KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY,

KUMASI, GHANA

LAND USE LAND COVER AND CLIMATE CHANGE IMPACTS ON AGRO-ECOSYSTEM SERVICES PROVISIONING IN RIVERINE AREAS OF PENDJARI RESERVE IN BENIN, WEST AFRICA

By

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A thesis submitted to the Department of Civil Engineering in partial fulfillment of the requirements of the degree

Doctor of Philosophy

In

Climate change and land use

August 2023

CERTIFICATION

I hereby declare that this submission is my own work towards the PhD degree in Climate Change and Land Use and that, to the best of my knowledge, it contains no material previously published by another person, nor material which has been accepted for the award of any other degree or diploma at Kwame Nkrumah University of Science and Technology, Kumasi or any educational institution, except where due acknowledgement has been made in the thesis.

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ABSTRACT

Examining the effects of land use and land cover change (LULCC) on biodiversity loss and human wellbeing in the Pendjari Reserve, a biodiversity hotspot in West Africa that has seen human disturbances for years, is the primary goal of this study. The study employed Landsat images and utilized the Random Forest classification software to analyze the dynamics of LULC for 1998, 2007, 2013, and 2020. The expected LULC for 2035 was projected using Terset 18.21. To learn more about household socio- economics characteristics and the advantages of trees in the townships from Tanguieta and Materi, information from 361 farmers was gathered. The influence of farm size, landholding, and district on tree diversity, tree species richness, and tree abundance, were examined as their combined impacts. The study unveiled notable alterations in LULC patterns, such as a reduced wooded savannah and a rise in shrub, cropland, and fallow land. Settlement areas experienced an increase in the studied period. The predicted results indicated an imminent slight decrease in wooded savannah, increase in shrub savannah, cropland, and fallow land, as well as a reduction of settlement areas in the future. Furthermore, farmers' preferences for tree and crop associations were assessed, with *Parkia biglobosa* identified as the tree species with the largest mean diameter at breast height (*dbh)* and height. At the same time, *Vitellaria paradoxa* had the highest height in Materi and Tanguieta. Tree benefits played a crucial role in selecting trees for agroforestry systems, with provisioning services followed by supporting services being the most common ecosystem benefits derived by local communities. Tree-crop associations varied among the farmers. The study examined the effects of tree conservation on agricultural output in agroforestry systems within the same study region as well as the impact of climate trends on critical crop yields. Findings revealed a substantial positive (warming) trend in temperature and a decrease in rainfall. There was a general positive warming trend observed between 1981 to 2020. Results showed that the lowest temperature positively and considerably impacted maize yields, while rainfall and relative humidity adversely affected respectively negatively and positively maize yields. The minimum temperature and relative humidity had a positive and substantial impact on sorghum. The maximum temperature and relative humidity negatively impacted cotton yield, but rainfall had affected positively cotton yields. Maximum and minimum temperature positively and significantly impacted cowpea yields. The Exponential regression model indicated that soil physicochemical characteristics and distance between tree and crop were the primary variables influencing crop yields in agroforestry systems. Furthermore, the study demonstrated that the maximum carbon stored by wooded savannah was projected to be 494,198.1 Mg C ha^{-1} in 2050, which decreased to 387,059.4 Mg C $ha\text{-}^{1}$ in 2020 and 387,047.2 Mg C $ha\text{-}^{1}$ in 2035. The lowest value of carbon is projected to be sequestered from 2020 to 2035, over a period of fifteen years. The highest gain and loss of projected carbon to sequestered for the period 2020 - 2050 is 108,947 Mg C ha^{-1} and -57, 996 Mg C ha^{-1} and the period 2035 -2050 is 108878 Mg C ha^{-1} and -57984.6 Mg C ha^{-1}, respectively. Conversely, the lowest gain and loss were anticipated from 2020 to 2035, with value of 845.56 Mg ha^{-1} and -47.52 Mg C $ha\text{-}^{1}$, respectively.

DEDICATION

I dedicate this study to the individuals and entities who have significantly shaped my life and work.:

- *God, who is the ultimate source of my life and work, and to whom all credit and glory belong.*
- *My father, Mahouwè MAKPONSE, and mother Lèbiwin AKPOVI, for their love, support, and guidance throughout my journey.*
- *My wife, Ella sèdé MAFORIKAN, for her unwavering encouragement and understanding.*
- *Professor. Marc T. KPODEKON and Mrs. Nonlèhouè AWEKE, for their valuable mentorship and contributions to my academic growth.*
- *My beloved children, Gbèhounou Pierre Cani, Gbènagnon Emmanuelle, and Houénafon Joseph Lawrence, whose presence and love have been a constant source of inspiration.*
- *To all of you, my dear friends and supporters, I have faith that you will achieve even greater things with the grace of God.*
- *Lastly, a heartfelt thank you to everyone who has guided my path to success in life.*

ACKNOWLEDGEMENTS

Completing this thesis has been demanding and lengthy, and I am deeply grateful to the numerous individuals who supported me throughout this journey. Without the assistance of many, I would not have been able to reach this milestone. I am immensely grateful to my supervisor, Prof Stephen Adu Bredu, from CSIR-Forestry Research Institute of Ghana (FORIG), for his invaluable guidance and unwavering support, which motivated me to undertake this thesis.

I would also like to express my appreciation to Prof Romain Glèlè Kakaï, Head of the Laboratory of Biomathematics and Forest Estimations (Labef) at the Faculty of Agronomic Sciences, University of Abomey-Calavi, and Prof Wilson Agyei Agyare from the Agricultural and Biosystems Engineering Department of the Kwame Nkrumah University of Science and Technology, Kumasi, Ghana. Their contributions and encouragement have been instrumental in shaping this research.

Their mentorship and advice were instrumental in shaping the outcome of this study. Additionally, I am grateful to Prof Jens Gebauer from Rhine-Waal University of Applied Sciences (HSRW), Prof Lawrence Damnyag of FORIG, Prof Sampson Kwaku Agodzo, and Dr. Enock Bessah from the Agricultural and Biosystems Engineering Department of the Kwame Nkrumah University of Science and Technology, Kumasi Ghana, for their unwavering support, which propelled me to achieve this significant milestone.

I sincerely grateful Dr. Emille Padonou, Dr William Amponsah, Dr. Nat Owusu Prempeh, and Dr. Stephen Oppong Kwakye for their invaluable advice. Special recognition goes to the Vice Chancellor of Kwame Nkrumah University of Science and Technology and her dedicated staff for their generous assistance and continued support in resolving students' challenges. I also express my gratitude to the staff of

WAS-CAL/KNUST and all the lecturers, especially Prof Wilson Agyei Agyare, GRP-CCLU Director, and Prof Eric Furko, Coordinator, for their accessibility and willingness to listen and guide students.

I cannot overlook the unwavering encouragement, collaboration, and administrative support provided by our mother, Theresah Sarpong Peprah. I appreciate the financial support provided by the German Federal Ministry of Education and Research (BMBF). Also acknowledged are Blaise Egbéton, Mrs. Aissè Nicole, and Mr. Augustin Kombeto for their support during the data collection and soil sample preparation.

Furthermore, I would like to express my appreciation to all my former and current colleagues at WASCAL/GRPCCLU, Bach 4, particularly Charles Sanou, Habibatou Thiam, (David) Dakéga Saberma Ragatoa, Ismail Koné, Alou Traore, Georges Dorda, Jacob Amoako, Franz Alex Guezi, Christopher Uche Ezeh, and Jalamang Camara, for fostering a collaborative and supportive working environment.

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LIST OF ABBREVIATIONS AND ACRONYMS

AGB: Aboveground biomass

AIC: Akaike information criterion

CD: Change detection

DBH: Diameter at breast height

ETM+: Enhance thematic mapper plus

FAO: Food and Agriculture Organisation

GHGs: Green House Gases

GIS: Geographic Information System

GPS: Global positioning system

IPCC: Intergovernmental Panel on Climate Change

OLI: Operational land imager

LULCC: Land use and land cover Change

NDVI: Normalised Difference Vegetation Index

REDD+: Reducing Emissions from Deforestation and forest Degradation)

TM: Thematic Mapper

USGS: United States Geological Survey

UTM WGS84: Universal Transversal Mercator World Geodetic System 1984

CHAPTER 1:GENERAL INTRODUCTION

1.1.Background

Ecosystems are crucial in supporting local economies, ensuring food security, providing forest products, preserving biodiversity, and providing various ecosystem services (Agbani *et al.,* 2018). The Millennium Assessment initiated extensive research on ecosystem services (Cao *et al.,* 2021). Human activities impact land cover, temperature, biogeochemical cycles, biodiversity, and ecosystem services as the population rises (Reyers *et al.,* 2013). Detecting and monitoring changes in land use and land cover (LULC) is therefore critical to understanding the consequences for ecosystem services at various scales. Ecosystem services contribute to human well-being, including provision, regulation, and cultural services (Kandziora *et al.,* 2013). However, climate change and land use change pose substantial risks to biodiversity and natural ecosystems. Temperatures have risen by 0.7°C in recent decades, with forecasts indicating a future increase ranging from 1.1°C to 6.4°C (IPCC, 2013). In the past century, precipitation has experienced an average increase of 2%, which is expected to continue. Africa has been warming, with temperature predicted to increase by 0.2°C- 0.5°C every decade (IPCC, 2001).

Precipitation patterns have also become more variable. Aside from climate change, land use change has emerged as the critical factor influencing ecosystem service supply (Hoyer & Chang, 2014). Land use change, directly or indirectly, modifies ecosystems' content and layout, impacting their potential to provide services (Cao *et al.,* 2021). The Convention on Biological Diversity (CBD) has established a fundamental goal for 2020: managing biodiversity to improve the supply of ecosystem services. Target 14 of The Convention on Biological Diversity (CBD) is committed to preserving ecological services to enhance livelihoods and wellbeing, focusing on the needs of women, indigenous peoples, and local communities (Paing *et al.,* 2022). Target 15 broadly addresses climate control. The ratification of the CBD by over 90% of African nations demonstrates a high level of commitment to preserving ecosystem services while simultaneously addressing poverty in these countries (Maes *et al.,* 2012).

Consequently, research is needed to comprehensively assess the advantages of ecosystem services to humans, taking into account monetary and non-monetary valuations. This research should also identify critical areas that require conservation efforts and places where good management of ecosystems would offer the most excellent benefits in terms of ecosystem services. Furthermore, it is essential to assess the patterns of ecosystem degradation and decline and the consequences of providing ecosystem services (Reyers *et al.,* 2013).

Understanding the impact of land use and climate change on ecosystem services is crucial at the global, regional, and local levels. This knowledge is critical for developing alternative management techniques and policies that promote sustainable resource utilization. According to Reid *et al.,* (2005), by 1990, more than of specific biomes, such as tropical and subtropical forests, had undergone alterations, leaving only 23 % of the original forests in their natural state. Due to the growing human population and resource demands, natural habitats are still being converted into agricultural land, pastures, plantations, urban areas, and infrastructure. The most common type of land use, accounting for roughly one-third of the planet's land surface (excluding Greenland and Antarctica), is agriculture. Most arable land is cultivated, while the remaining areas are unsuitable for food production due to high altitude, steep slopes, flat terrain, aridity, or extreme cold (McGuire, 2015). The agricultural sector primarily contributes to biodiversity loss, albeit with complex effects on various species. Food production plays a critical role in the decline of ecosystems, particularly affecting tropical forests (Zwane, 2007). During the previous twenty years, there has been a 12 % expansion in the worldwide arable land area (Kertész *et al.,* 2019), with a significant portion attributed to the transformation of natural ecosystems (Dudley & Alexander, 2017). During the 1980s and 1990s, forests served as the primary source of new agricultural land (Acheampong *et al.,* 2019), and this trend continues to persist (Ayoo, 2022). Between 2010 and 2015, the annual reduction in tropical forest cover reached 5.5 million hectares (Raj *et al.,* 2022).

Understanding the importance of the agroecosystem service concept is essential for managing and making decisions about farms. Additionally, there are still difficulties in accurately defining and pricing these services (Gómez-Baggethun & Barton, 2013) and estimating, mapping, and modeling the spatial distribution of ecosystem services, supply, and demand (Liu *et al.,* 2023).

1.2. Problem Statement and Justification

With the projected global population reaching nine billion by 2050, there is growing anticipation for agricultural production systems to fulfill the increasing food demands (Giller *et al.,* 2021). The per capita increase in agricultural production, averaging 1.8 percent per year, corresponds to Africa's population growth rate of 3.1 percent annually. In 1995, approximately 90 % of Africa's population comprised rural households engaged in subsistence farming, relying solely on wood and charcoal for energy. Deforestation in Africa between 1981 and 1995 was estimated at 1.3 million hectares per year, with the annual destruction of savannah forests predicted to reach 2.3 million hectares (Ameixa *et al.,* 2020). Food poverty and dwindling forests have been exacerbated further by environmental issues caused by pests and diseases, compounding precarious ecological circumstances (Ameixa *et al.,* 2020). Innovative approaches are urgently needed to enhance crop production and ensure stability for smallholder farmers. Identifying practical innovations and practices is paramount in achieving this objective. It is crucial to build new knowledge to support these endeavors. The limitations of the existing agricultural intensification and growth paradigm have been discussed. This strategy strongly depends on the increased use of capital inputs such as fertilizers and pesticides (Li *et al.,* 2023). Due to advancements in crop types, herbicides, and mineral fertilizers, a significant increase in agricultural yields was seen in the second half of the 20th century (Jacquet *et al.,* 2022). However, the intensification of land use has had detrimental effects on soil organic matter and biodiversity (Dang *et al.,* 2021). While land-use intensification has increased yields, it has also reduced carbon stocks in soil and above-ground vegetation. Once a critical point is reached, researchers anticipate a decline in carbon stock and output (Gessesse *et al.,* 2020). Agriculture intensification, marked by the excessive utilization of agrochemicals and annual fertilizers exceeding 200 million tons, drives this trend (Sharma *et al.,* 2019). Systemic insecticides have been shown to severely harm invertebrates, amphibians, and birds (Chagnon *et al.,* 2015), and other pesticides, fungicides, and herbicides often used in conjunction have also been the subject of similar concerns (Rajak *et al.,* 2023), fungicides, and herbicides (Schuhmann *et al.,* 2022). Pesticides tend to disperse widely from their point of application (Tudi *et al.,* 2021). Glyphosate consumption is dominated by herbicide-resistant genetically modified (GM) crops, accounting for 56 % (Benbrook, 2016), and the increased tolerance of these crops implies a higher probability of future application rate escalation (Allison & Goulden, 2017). These findings contribute to understanding why biodiversity in and around agricultural landscapes continues to decline (Landis, 2017). The emergence of environmental damage and challenges related to economic feasibility are central issues associated with this agricultural model (Schindler *et al.,* 2016).

According to Nin *et al.,* (2007) and Sossou *et al.,* (2014), 75 % of the population of Benin is employed in agriculture, which generates around 29.89 % of the country's GDP and 80 % of its exports. Implementing improved technologies is required to increase small-scale farmers' production because they are crucial to Beninese agriculture (Diao *et al.,* 2019; Nonvide, 2021). However, traditional farming methods that typically support diverse biodiversity have been supplanted by intensive farming systems, which range from small-scale agriculture to massive monoculture plantations (Kremen *et al.,* 2012). Conversely, increasingly intensive systems, from small-scale farming to massive monoculture plantations, have replaced traditional farming techniques renowned for aiding biodiversity conservation (Chandler *et al.,* 2013).

Agroforestry systems have received particular attention as potential sustainable land management technologies. These systems offer private benefits to farmers by improving soil fertility and structure, preserving soil and water, fostering soil fauna activity and diversity, and bolstering processes of the element cycle (Lorenz & Lal, 2014). According to studies, agroforestry systems boost agricultural production systems' productivity and stability (Brown *et al.,* 2018). Agroforestry presents substantial opportunities to enhance agricultural yields, improve food security, and reduce the susceptibility of farming systems to climate risks. Additionally, the widespread adoption of agroforestry as a method of sustainable land management can considerably support environmental public goods, particularly the reduction of climate change (Castle *et al.,* 2022). Agroforestry system contributes substantially to climate change mitigation by effectively reducing greenhouse gas emissions, accounting for 14 % of global emissions (Lynch *et al.,* 2021).

Furthermore, the sector enhances the removal of greenhouse gas emissions through sequestration (Nunes *et al.,* 2020). Soil carbon sequestration alone has the potential to represent 89 % of the technical mitigation capacity of agriculture (Shukla *et al.,* 2019). Improving productivity can reduce the need for further land conversion to agriculture, thereby minimizing direct greenhouse gas emissions from agricultural activities (Gołasa *et al.,* 2021).

1.3.Objectives

This research aim is to model the impacts of LULC and climate change on the provision of agroecosystem services in the riverine area of the Pendjari Reserve, in Benin, West Africa.

The specific objectives were to:

i. analysis spatiotemporal land use land cover change from 1998 to 2020,
ii. determine farmer's preferences for tree and plant associations for agroforestry systems as an adaptation strategy to climate change,
iii. assess climate variability and tree protection impacts on crop production in the agroforestry system,
iv. model carbon sequestration potential in agroforestry system.

1.4.Research Question

i. What are the LULC patterns in the riverine area of Pendjari Reserve from 1998 to 2020?
ii. What are farmers preferred tree species and associations in agroforestry system in the study area?
iii. Do climate change and tree conservation affect crop yield in agroforestry systems?

iv. Does carbon sequestration potential vary in agroforestry systems?

1.5.Dissertation outline

There are seven (7) chapters in the dissertation. Background information, the problem statement and justification, the objectives and the study questions are presented in Chapter 1. The second chapter presents the literature review, defining keywords used in the study and summarizing previous research relevant. In Chapters 3, 4, 5, and 6, the study presents the first, second, third, and fourth objectives, respectively, presenting introduction, methodology, results discussion findings, and conclusions in a manuscript format. Finally, Chapter 7 provides the conclusion and recommendations of the study.

CHAPTER 2:LITERATURE REVIEW

2.1 Ecosystem and Agroecosystem Service

The concept of ecosystem services has established a link between ecosystem functioning and the benefits they offer humans, providing a valuable tool for integrating environmental considerations into decision-making processes (Zhang *et al.,* 2022). The Common International Classification of Ecosystem Services (Grima *et al.,* 2023) defines ecosystem services as climate regulation. The Millennium Ecosystem Services (Carpenter *et al.,* 2009) describe them as the goods and services nature provides that contribute to human wellbeing. A variety of categories are covered by these services, which include provisioning services (such as food and fuel), regulatory services (including flood control and carbon sequestration), and cultural services (such as aesthetic value and outdoor recreation) (Rippy *et al.,* 2022). Ecosystem services are the advantages people obtain from ecological systems, directly or indirectly (Vallecillo *et al.,* 2019). The ability to model, measure, map, and value ecosystem services is critical for successful natural capital management and policymaking. However, rising public demand and global environmental changes jeopardize ecosystems' ability to offer these services (Li *et al.,* 2022). Many ecosystem services are declining, and this trend will likely worsen in the following few years (Cui *et al.,* 2022). It is vital to highlight that an increase in supplying services may come at the price of other ecosystem services, and unsustainable management methods may jeopardize their future provision. In the past decade, researchers have significantly advanced in understanding how ecosystems generate services and quantifying the economic value associated with these services (Cao *et al.,* 2021). The sustainability of agroecosystems and their contribution to ecosystem services are receiving more attention in light of their effects on monetary values and human well-being (Bethwell *et al.,* 2021). Given the complex interrelationships between the environment, agriculture, and society, identifying the linkages between agricultural ecosystems and ecosystem services can be challenging (Vidaller *et al.,* 2022). Soil preservation, food production, and aesthetic value are essential ecological services agroecosystems offer.

Additionally, they benefit from the ecosystem services provided by non-agricultural ecosystems, such as pollination. The management practices implemented within agricultural systems can impact the provision of ecosystem services in non-agricultural systems. Both climate change and land use change are recognized as major environmental issues on a global scale (Nepstad *et al.,* 2013). Agriculture, closely intertwined with social, economic, and cultural activities, presents various opportunities to tackle these challenges.

2.2 Agroforestry system

Multiple definitions of agroforestry vary. Agroforestry integrates trees, crops, and livestock within a land management system, providing a wide array of ecosystem services and bridging the gap between agriculture, forestry, and livestock (Paudel & Shrestha, 2022). According to Watling *et al.,* (2017), agroforestry has been practiced in the Amazon forests for over 600 years, involving the temporary clearance of forests to cultivate palm trees, maize, squash, and establish settlements. Pantera *et al.,* (2021) define agroforestry as integrating perennial forests with crops to optimize land use intensively. Both climate change and land use change are recognized as major environmental issues on a global scale (Nepstad *et al.,* 2013). Integrating agroforestry enhances land productivity and resource utilization efficiency and contributes to vital ecosystem services. There are four main types of agroforestry systems identified (Dhakal et al., 2012):

i. **Farmland tree systems:** These include both planted and retained trees on farmland, serving multiple purposes such as food production, income generation, soil improvement, and environmental enhancement. They also provide shade during harsh weather conditions**;**

ii. **Parkland systems:** These systems feature well-established scattered trees like *Parkia biglobosa, Vitellaria paradoxa, Tamarindus indica, and Azadirata indica* on cultivated and recently fallowed land;

iii. **Alley cropping:** This agroforestry system involves cultivating annual crops in strips between rows of trees or shrubs;

iv. **Windbreakers and shelter belts**: These systems utilize specific tree species, including *Azadirachta indica, Anacardium occidentale, Mangifera indica*, and *Khaya senegalensis*, primarily to control wind erosion.

Agroforestry systems can further be classified as:

i. **Agro-silvicultural**: These resemble shifting cultivation practices, but instead of fallow vegetation, economic trees with gestation periods equivalent to the fallow period are planted;

ii. **Silvopastoral**: This system combines animal production with trees and pastures;

iii. **Mixed farming:** This system represents the traditional agroforestry practices commonly employed by farming communities.

2.3 Carbon sequestration, climate change mitigation and adaptation in agroforestry system

The Kyoto Protocol of 1997 established targets for industrialized countries (Annex B) to limit the emissions of six greenhouse gases (CO2, CH4, NO2, and fluorinated gases) from 2008-2012. The framers explicitly offered Annex B countries a choice to partially fulfill their reduction commitments by actively engaging in reforestation, forest management, and other agricultural land management practices. These activities, collectively called land use, land cover change, and forest management measures (LULUCF), offer avenues to fulfill their targets. Reducing atmospheric CO2 can contribute to stabilizing atmospheric CO2 concentrations and mitigating climate change. Assessing the spatial distribution of biomass and the amount of carbon stock is necessary for carbon balance calculations (Sun *et al.,* 2020). Above-ground biomass plays a significant role in biomass carbon and is crucial for carbon inventory in most mitigation projects conducted under the Kyoto Protocol (Meragiaw *et al.,* 2021).

However, increasing carbon emissions and global warming raise interest in estimating ecosystem carbon stocks. In mitigating climate change, ecosystems are essential in absorbing carbon from the atmosphere. Czcz *et al.,* (2018) define ecosystem services as climate control, and indicators include carbon storage and sequestration. Carbon sequestration, recognized as an effective strategy for mitigating climate change, has long been associated with afforestation and reforestation of degraded natural forests (Nunes *et al.,* 2020). Agroforestry, in particular, offers distinct advantages in this regard. Integrating trees within agricultural systems not only reduces reliance on natural forests for fuel but also provides additional benefits such as livestock forage, enhanced soil fertility, erosion control, prevention of waterlogging, regulation of stream and river acidification and eutrophication, and increased local biodiversity (Jinger *et al.,* 2023). With variations caused by environmental and socioeconomic conditions, agroforestry systems in humid tropical climates can store over 70 Mg ha-1 of carbon in the top 20 cm of soil (Yasin *et al.,* 2021). According to the tree species chosen and the region, agroforestry's ability to trap carbon differs (Siarudin *et al.,* 2021; Ma *et al.,* 2019). The quantity of carbon stored within agroforestry systems is also greatly influenced by the design and operation of various system components (Sollen-Norrlin *et al.,* 2020; Komal *et al.,* 2022).

However, with increasing carbon emissions and global warming, there is a growing need to accurately assess carbon stocks within ecosystems (Enríquez-de-Salamanca, 2022). By absorbing carbon dioxide from the atmosphere, ecosystems serve a critical role in preventing climate change, and climate control, including carbon storage and sequestration, is acknowledged as an essential ecosystem service (Nunes *et al.,* 2020; Baskent, 2020). Degraded natural forests' regeneration and afforestation have long been recognized as viable strategies for reducing climate change (Ma *et al.,* 2019). Agroforestry systems contribute to these efforts by reducing pressure on natural forests, providing livestock forage, enhancing soil fertility, preventing erosion, controlling waterlogging, addressing water body acidification and eutrophication, and promoting local biodiversity (Jinger *et al.,* 2023).

It is crucial to examine the specific type of agroforestry system and its influence on trees' carbon source or sink function. According to Fahad et al., (2022), systems that promote the association of trees and crops act as net sinks, while systems that combine crops, trees, and animals have the potential to become sources of greenhouse gases. Agroforestry systems provide synergies between adaptation and mitigation measures, with a projected technical mitigation potential of 1.1–2.2 Pg C in terrestrial ecosystems over the next 50 years (Roe et al., 2021). However, inconsistent methodologies and inherent variability in estimating carbon storage potential in agroforestry systems have made comparisons challenging (Panwar et al., 2022). Further research is needed to identify specific agroforestry practices that show potential for carbon sequestration (Tan & Kuebbing, 2023). Global carbon storage varies across ecoregions and different agroforestry systems is showing in Table 2.1 (Murthy et al., 2013; Agbotui et al., 2023).

Table 2.1 Carbon storage potential of agroforestry systems in different ecoregions of the world; Source: Murthy *et al.,* (2013)

Continent	**Ecoregion**	**System**	**Potential (Mg C ha^{-1})**
Africa	Humid tropical high	Agrosilvicultural	29-53
South America	Humid tropical low dry lowlands		39-102 39-195
Southeast Asia	Humid tropical dry lowlands		12-228 68-81
Australia	Humid tropical low	Silvopastoral	28-51
North America	Humid tropical high humid tropical low dry lowlands		133-154 104-198 90-175
North Asia	Humid tropical low		15-18

2.4 Land use land cover change

The loss of wetlands and the accompanying ecological services during the 20th century was caused mainly by changes in land use (de Silva *et al.,* 2023). One main factor driving global change affecting human well-being is the shift in land cover (Hussain *et al.,* 2022). Altering the composition or condition of land cover has implications for climate (Thiam *et al.,* 2022). Land serves as a space for various human activities, and its use, known as "land use," varies depending on its intended purposes, such as food production, shelter provision, recreation, material extraction and processing, and the inherent biophysical characteristics of the land itself. Intensifying crop production in fertile regions and abandoning farming in less favorable areas have global effects on natural and cultivated ecosystems (Djihouessi *et al.,* 2022). Understanding how it varies is essential for land and subsurface studies, which refer to the biophysical state of the Earth's surface as "land cover." Previous research mainly concentrated on the tangible consequences of land cover change. Nevertheless, because of land use and cover changes, scientists now understand how land surface processes contribute to climate change.

Furthermore, Dimobe *et al.,* (2022) analyzed soil degradation, while Assogbadjo *et al.,* (2022) looked at the ability of biological systems to support human requirements. Ganglo (2023) assessed the global effects of land cover change on biotic diversity. According to the literature on land use and land cover change, significant agricultural land use changes continue to occur globally. Twenty percent of cropland, 19 percent of grassland, and 27 percent of rangeland experienced persistently deteriorating productivity trends between 1998 and 2013 (Kombienou *et al.,* 2022). Population growth, particularly the increasing demand for food, fuel, and shelter, coupled with rising affluence and changes in food consumption patterns towards land-intensive commodities like meat and dairy products, contribute to these changes (Elliot *et al.,* 2022). Recent research indicates that the expansion of agriculture in West Africa is causing the loss of savannas and forests (Radwan, 2021). However, evaluating changes in land use and land cover necessitates a more thorough examination of the underlying mechanisms. Modelling the system, developing, and verifying the connections between driving forces and land-cover change (Biaou *et al.,* 2022) can better comprehend these change processes.

2.5 Climate change

One of the most critical global issues is climate change, which seriously threatens the economy and ecology (Bhattacharya, 2023). The repercussions of climate change are particularly severe for developing nations in Africa (Djihouessi *et al.,* 2022). The fact that these resource-constrained nations face the burden of climate change while also finding it difficult to adapt is depressing (Gnansounou *et al.,* 2022). According to (Opute and Maboeta 2022), many plant species thrive at an ideal temperature of 33°C.

However, higher atmospheric CO_2 concentrations may offset any potential increases in agricultural production as decreased productivity at higher temperatures could come into play.

Furthermore, the anticipated rise in the frequency of extreme weather events poses a significant global concern for agricultural output (Mounirou, 2022). Enhancing crop modeling under increasing temperature and changing climate conditions and improving crop yield estimates are essential for developing effective adaptation strategies (Minoli *et al.,* 2022). Climate shifts severely impact crop production worldwide (Pickson & Boateng, 2022). Carr *et al.,* (2022) suggest that climate change may have already slowed the growth of food yields by 1-2% per decade during the twentieth century. However, it is essential to note that different climatic factors influence agricultural output differently.

In Benin, maize, sorghum, cowpea, and cotton are the most significant arable crops (Rege & Sones, 2022). These crops are primarily cultivated for food purposes, with maize being a crucial crop selected for intensive development by the government of Benin (Akpa *et al.,* 2023). The northern Guinea Savannah region is home to the opaque sorghum beer known as tchoukoutou in Benin and by other names in other parts of West Africa (Kohnert, 2020). Millions of West Africans depend heavily on cowpea, an important grain legume (Anago *et al.,* 2021). Its leaves and grains are highly nutritious, with protein contents ranging from 27 % to 43 % and 21 % to 33 % in grains (Mekonnen *et al.,* 2022). A significant portion of Benin's national economy, 14% of the GDP, and 30 % to 40 % of export revenue come from the cotton industry (Chabi Simin Najib et al., 2022). Temperature fluctuations beyond the optimal range for maize, cowpea, sorghum, and cotton significantly impact yield variability compared to temperature variations below the optimal range and soil water deficit (Mogale *et al.,* 2022). Additionally, water scarcity is a significant factor contributing to changes in agricultural output across the country (Hejazi *et al.,* 2023). Observed weather fluctuations can explain more than 50 % of the variation in rice and soybean production in countries like Japan, South Korea, and Argentina, surpassing the impact of fluctuations in irrigated land (Hejazi *et al.,* 2023).

Fluctuations in weather patterns play a significant role in explaining over 50 % of the variations observed in rice and soybean production in countries such as Japan, South Korea, and Argentina. The sensitivity of these crops to weather conditions surpasses the influence of fluctuations in irrigated land.

2.6 Modelling approach

2.6.1 Ecosystem Services modelling

Yang *et al.,* (2022) employed an Invest analysis to demonstrate that land management scenarios prioritizing regulatory services such as carbon sequestration, flood control, and water quality had the highest levels of biodiversity. Cimon-Morin *et al.,* (2013) highlighted the positive connection between biodiversity and the delivery of services, emphasizing the need for biodiversity-focused initiatives. However, they found that safeguarding the benefits alone did not achieve biodiversity conservation goals. Similarly, Lanzas *et al.,* (2019) observed in their study that conservation efforts for biodiversity increased service supply, even when they aimed to protect at least 30% of vital ecosystem service flows by lowering biodiversity objectives. It is crucial to understand and effectively communicate the trade-offs inherent in management practices driven by different goals (Green & Healy, 2022). The concept of emitters paying to prevent deforestation in other regions as a win-win policy underscores the importance of embracing the complexities of trade-offs among social and ecological actors for sustained conservation success (Wassenius & Crona, 2022). Jiang *et al.,* (2022), in a meta-analysis of ecosystem service case studies, argued that considering trade-offs from the project's inception increases the likelihood of win-win outcomes compared to programs striving for an exclusive "win-win" scenario. The applicability, data requirements, costs, and usability of the many approaches and software tools available for calculating the value of ecosystem services vary (Chalkiadakis *et al.,* 2022). The supply of ecosystem services can be calculated for various land use scenarios, including carbon sequestration models for 2020, 2035, and 2050, using the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) software (Jiang *et al.,* 2022).

2.6.2 Land use land cover change

Summarized is the state of land-use modelling, with a particular emphasis on the usability, applicability, and accessibility of modelling tools, especially concerning land-use change as a driver of changes in carbon sequestration. To analyse the effects of land-use change and degradation on biodiversity and environmental services, it attempts to help them make well-informed judgments regarding the capacity requirements and possibilities for using land-use models. Examining future effects on ecosystem services, weighing the trade-offs between various land-use demands, and guiding decision-making processes are possible thanks to land-use models. Accurately predicting future changes is difficult due to the complicated relationships between ecosystem services provided by ecosystems and land use. However, these modelling efforts can provide valuable information for prioritizing conservation actions, particularly on larger scales. Numerous land-use models operate at different scales, from local to global, and provide varied levels of precision. Geographic land-use models widely classify various forms of land use based on the land's biophysical, infrastructural, and suitability (Adugna et al., 2022).

Table 2.2 Description of Invest model Land use and their output in terms of ecosystem services

reference	**Location**	**Land use model**	**Ecosystem Services model**	**Ecosystem services included**
Nelson et al.(2010)	Global	The estimated change in farmland and urban land is distributed spatially.	InVEST	Carbon, habitat, and water
Shoyama & Yamagata (2014)	Japan	Dyna-CLUE	InVEST	Habitat quality, carbon emissions, wood, and water
Lawler et al. (2014)	United States	Econometric LU model	Models of soil carbon sequestration, timber output, and behavioral affinities	Habitat, food production, and carbon
Geneletti (2013)	Chile	IDRISI Land Change Modeler	InVEST	wood production, carbon sequestration, habitat preservation, water purification, and soil conservation
Polasky et al. (2011)	Minnesota, USA	Maps depicting a a recent shift in land cover	InVEST	Carbon, water quality
Swetnam et al. (2011)	Eastern Arc Mountains, Tanzania	Rule-based land-cover maps	Rule-based	Carbon
Heubes et al. (2012)	Northern Benin	LandSHIFT	Species distribution Model (Biomod)	NTFP
Van Soesbergen &Arnell (2015)	East Africa, Mekong, Andes	LandSHIFT	Ecosystem Functions (Kienast *et al*. 2009)	Bundled provisioning and regulating services
Zulian et al. (2014)	EU	EU-CLUE Scanner 100	ESTIMAP framework	Crop pollination, coastal protection, outdoor recreation, air quality regulation

CHAPTER 3:SPATIAL-TEMPORAL LAND USE LAND COVER CHANGE FROM 1998 TO 2020 IN THE RIVERINE AREA OF PENDJARI RESERVE IN BENIN

Abstract

Changes in land use and land cover contribute to biodiversity loss and affect human well-being. Understanding this occurrence in the riverine area of Pendjari Reserve, for which anthropogenic activity has disturbed for thousands of years and is now acknowledged as an important biodiversity hotspot in West Africa, is crucial. The researchers used Landsat images from 1998, 2007, 2013, and 2020 to assess changes in land use and land cover (LULC) by employing the Random Forest classification in the ArcGIS program. Additionally, LULC projections for 2035 and 2050 was simulate using Terset 18.21. The results revealed significant changes in LULC patterns. From 1998 to 2020, the wooded savannah experienced consecutive decreases of 4.7 %, 8 %, and 11.5 % in 1998-2007, 2007-2013, and 2013-2020, respectively. On the other hand, shrub savannah increased by 10.5 % and 3.88 % during 1998-2007 and 2007-2013 before a decline of 1.17 %. Cropland initially decreased by 6.66 % from 1998-2007 but exhibited increases of 4.33 % and 11.1 % from 2007-2013 and 2013-2020, respectively. Fallow land experienced a rise of 0.77% and 0.83% for 1998-2007 and 2013-2020, followed by a slight decrease of 0.7 % from 2007-2013. Between 1998 and 2020, the settlement area expanded. Furthermore, there is a projection for the settlement area to decrease, emphasizing the importance of an African partnership for better land management in this study area.

Keywords: Land degradation, climate change, ecosystem, and human activities.

3.1 Introduction

Barbier and Hochard (2018) stated that land degradation is one of today's most urgent socioeconomic and environmental issues. The association between land degradation and the severity and prevalence of poverty in the population was highlighted in a special report by the Intergovernmental Panel on Climate Change (IPCC) (Shukla *et al.,* 2019). In drylands regions, a vicious cycle exists between land degradation and poverty due to population increases (van der Esch, 2017). Human activities, particularly the accelerated process of global urbanization, have led to rapid changes in land use and land cover (Rimal *et al.,* 2019; Minelli *et al.,* 2017).

Land degradation can alter ecosystems' structure and function in the short term, impacting ecosystem supply (Zhang et al., 2020; Martinez-Harms *et al.,* 2015). For example, societal development has disrupted the balance between ecosystem supply and demand. As a result, future land planning and the integration of ecosystem assessments have gained importance as research topics (Cortinovis & Geneletti, 2018).

Human activities threaten the world's ecosystems, which are under increasing pressure. Agriculture, while essential for sustaining the human population with food, disrupts ecosystem functioning and is a critical driver of global climate change affecting various

human-environment systems. Land cover composition and condition changes influence climate, biogeochemical cycles, and energy fluxes (IPCC, 2022).

Deforestation estimates for tropical regions, particularly West Africa, are scarce and uncertain (Lambin *et al.,* 2003). Bekasova (2020) states that by 1990, only 2% to 3% of the original forest resembling its natural condition had been preserved in various distinct biomes, including tropical and sub-tropical dry broadleaf forests. The conversion of natural habitats to agriculture, pastures, plantations, built areas, and infrastructure continues due to population growth and increased resource demand. This habitat degradation or loss severely affects populations and biodiversity, as habitat loss remains the greatest threat to biodiversity (Hanski, 2011).

In West Africa, ecosystems have suffered, leading to significant declines in wildlife populations (Janssens *et al.,* 2022). However, researchers have recognized Pendjari National Park in Benin as a successful conservation area (Bauer et al., 2020). Given that Pendjari National Park is the largest surviving protected savannah ecosystem in West Africa, Carvalho (2020) notes that it is a refuge for several threatened species. The vegetation within the park is highly dynamic and sensitive to land-use changes (Ogato *et al.,* 2021), with wildfires, grazing, slash-and-burn agriculture, and irregular rainfall being the dominant forms of disturbance affecting vegetation structure and physiognomy (El Bilali, 2021).

Analysis of land use and land cover change is essential for addressing issues in various areas, including changes to environmental services (Gilani *et al.,* 2022) and urban growth (Deng & Srinivasan, 2016). Understanding the relationships and interactions between natural and anthropogenic activities is vital, and change detection is essential in this regard (Wang *et al.,* 2021). The effects of urban growth on land use and land cover have been studied using change analysis (Rahimi, 2016), as have the effects of natural disasters and insect infestations on vegetation cover (Habibur-Rahman *et al.,* 2022). Cross-correlation analysis, image differencing, post-classification comparison (PCC), and image fusion-based land use change detection are some of the advanced techniques used by Geographic Information Systems (GIS) and remote sensing to observe changes in land use and land cover (Birhanu *et al.,* 2019). This study aims to

(i) assess the trends of land use change from 1998 to 2020 and (ii) project land use and land cover changes for 2035 and 2050

3.2 Material and Methods

3.2.1 Study Area

The study was conducted in the Pendjari Biosphere Reserve's riverine region, located in the Republic of Benin's northwest (10.30 to 11.30 °N; 0.50 to 2.00 °E). The Pendjari Biosphere Reserve (BRP) has two zones that are included in the study: the Zone of Controlled Occupation, where settlements and all agricultural activities are allowed, and the Hunting Zone, which permits medium-impact activities like the controlled harvesting of non-timber forest products and trophy hunting by tourists (Janssens *et al.,* 2022) (see Figure 3.1). About 340 km^2 is covered by the Zone of Controlled Occupation, while 1,750 km^2 is the Hunting Zone (Sinsin *et al.,* 2002). The BRP is made up of two main parts that together make up its 4,661.4 km^2 total area: the core zone, also known as the National Park of Pendjari (2,660.4 km^2), and the hunting zones, which include the hunting zones of Pendjari (1,750 km^2) and Konkombri (251 km^2) and are spread across four neighbouring countries (Benin, Burkina Faso, Niger, and Togo). The Materi and Tanguieta central administrative districts are part of the Reserve's geographic division. The Pendjari River and the Atacora mountain range form its northern, western, and eastern borders. The dry season in this Sudanese ecosystem lasts from October to May, and it is followed by the wet season, which lasts from June to September and has yearly rainfall between 800 and 1000 mm. The Reserve's vegetation is made up of open grasslands, tree savannahs, and smatterings of dry and gallery forests. Large carnivores and other animal species find refuge in these diversified settings (Sogbohossou *et al.,* 2014). The mean annual temperature is 27°C. The Reserve's boundaries are formed by the Tanguieta Porga and Tanguieta

Batia main roads. The Berba, Gourmantche, and Wama make up the three main ethnic groups in the area. In addition to the local farmers, Fulani pastoralists live in the majority of the towns; there are typically one to eight camps per town.

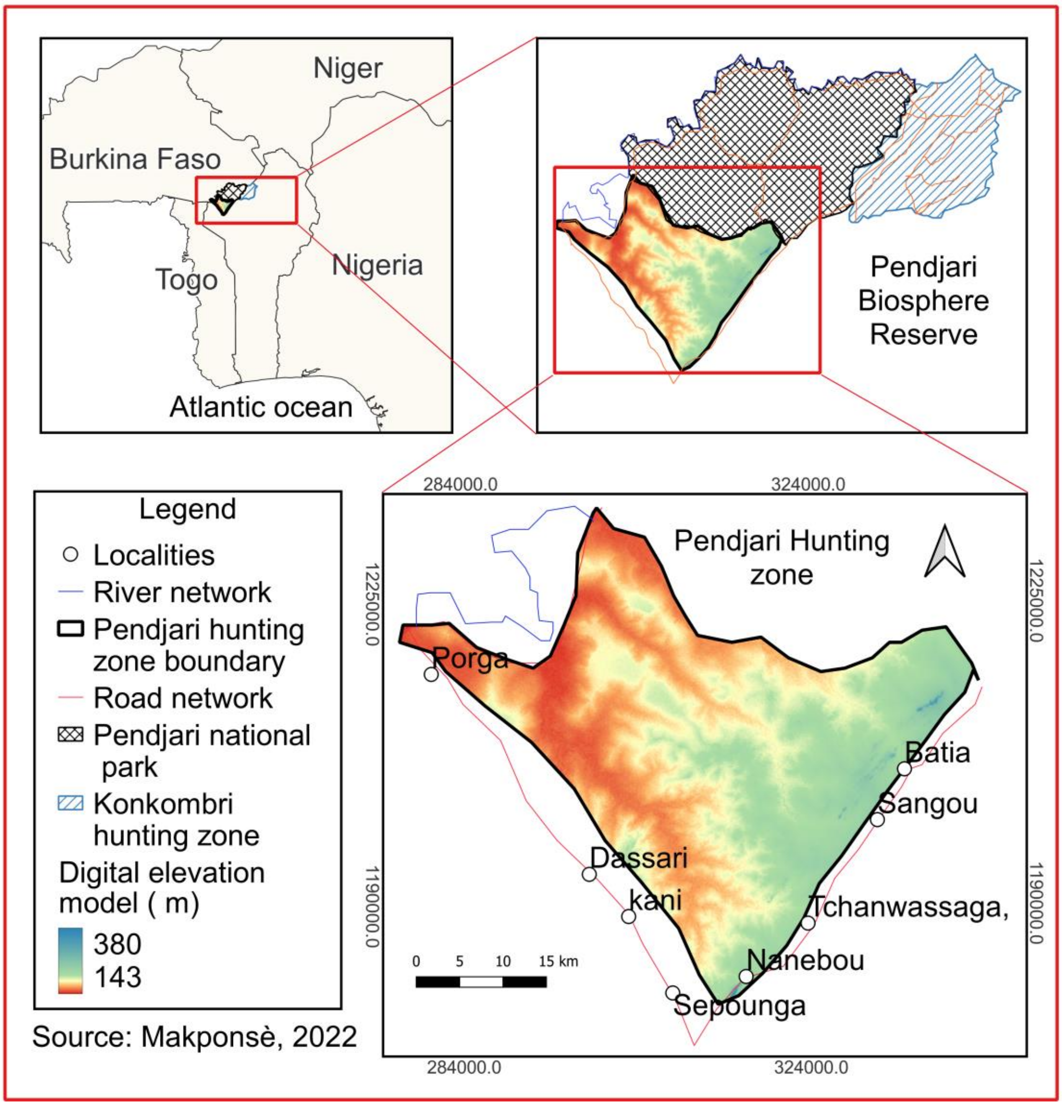

Figure 3.1 Map of riverine Pendjari Biosphere Reserve in the northern part of Benin

3.2.2 Land use change analysis

3.2.2.1 Data Pre-processing and Classification

The Pendjari hunting zone covers two scenes with path/row (193/052 and 193/053) Two sets of Landsat 7 ETM+, Landsat 8 OLI, and Landsat 5 TM data with 30 m resolution (Figure 3.2) were downloaded from the United States Geological Survey (https://earthexplorer.usgs.gov).

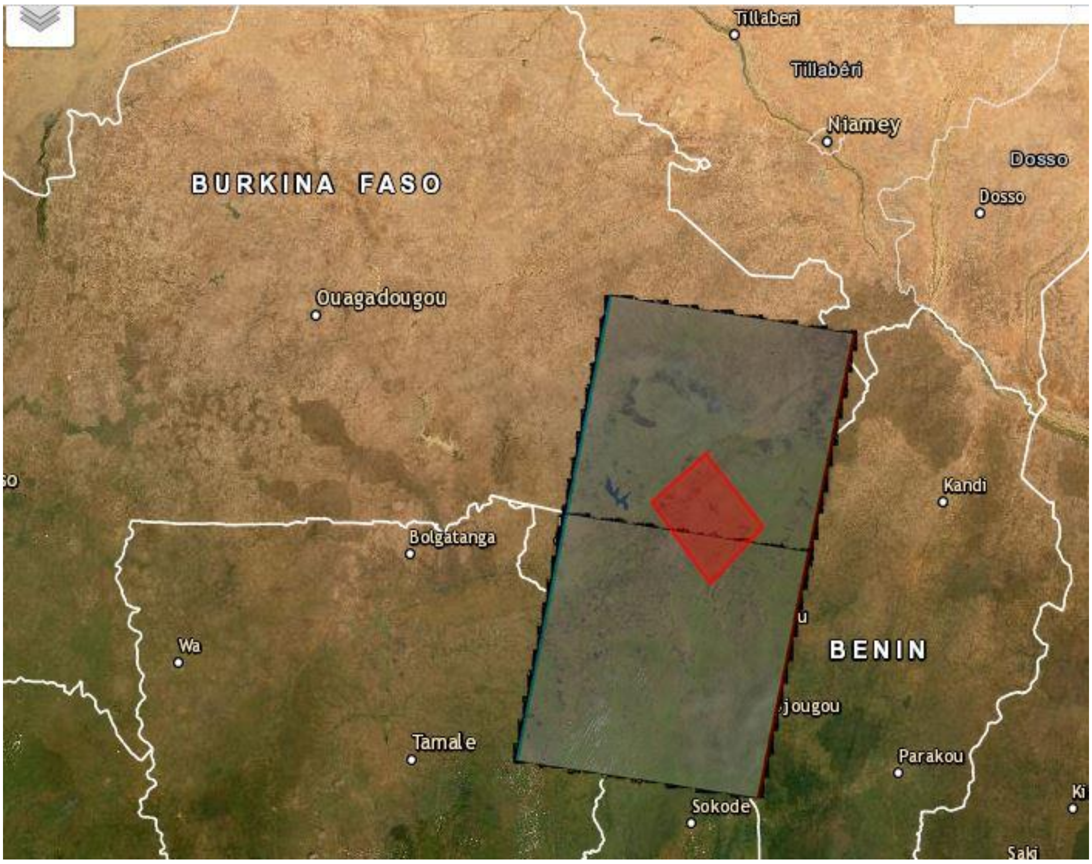

Figure 3.2 Screenshot of the two scenes image of Landsat that cover the study area

Data were acquired in November 1998, 2007, 2013, and 2020. The study period was chosen based on images with a cloud cover of less than 10% and the availability of two scenes for each Landsat (Table 3.1).

Table 3.1 Satellite images of the study area

Acquisition dates	Scene	Path/Row	Cloud cover (%)	Sensor type	Spatial resolution (m)
01/11/2020	1	193/052	0.0	OLI/TIRS	30×30
01/11/2020	2	193/053	0.0	OLI/TIRS	30×30
14/11/2013	1	193/052	0.0	OLI/TIRS	30×30
14/11/2013	2	193/053	5.92	OLI/TIRS	30×30
06/11/2007	1	193/052	0.0	ETM+	30×30
06/11/2007	2	193/053	0.0	ETM+	30×30
21/11/1998	1	193/052	6.0	TM	30×30
21/11/1998	2	193/053	3.0	TM	30×30

The pre-processing steps involved performing atmospheric correction, mosaic, and gap fill. The two scenes were mosaicked and clipped them to the study area. Five major land classes, namely wooded savannah, shrub savannah, fallow, cropland, and settlement, were used as in the classification scheme (Table 3.2).

Table 3.2 Major land use land cover types used and their descriptions

Number of Land use	LULC Types	Description
1	Wooded savannah	Areas that encompass dense trees, such as deciduous forests, evergreen forests, and mixed forests.
2	Shrub savannah	The upper story typically presents forms of vegetation with a completely grassy ground cover with sporadic trees, bushes, or palms.
3	Cropland	This group includes irrigated regions, commercial farms with a focus on sugarcane plantations and sesame farming, as well as areas used for perennial and annual crops.
4	Follow	The secondary succession of abandoned farmland facilitates the rehabilitation of land for resumed cropping in regions where shifting cultivation is practiced.
5	Settlement	Built-up, residential area

Both the unsupervised and supervised classifications were used for this study. The unsupervised classification was conducted to gain insights into the general land cover classes of the study area. To train the model, we performed supervised classification using the random forest (RF) machine learning algorithm in QGIS software version 3.16. showing in the screen shot (Figure 3.3).

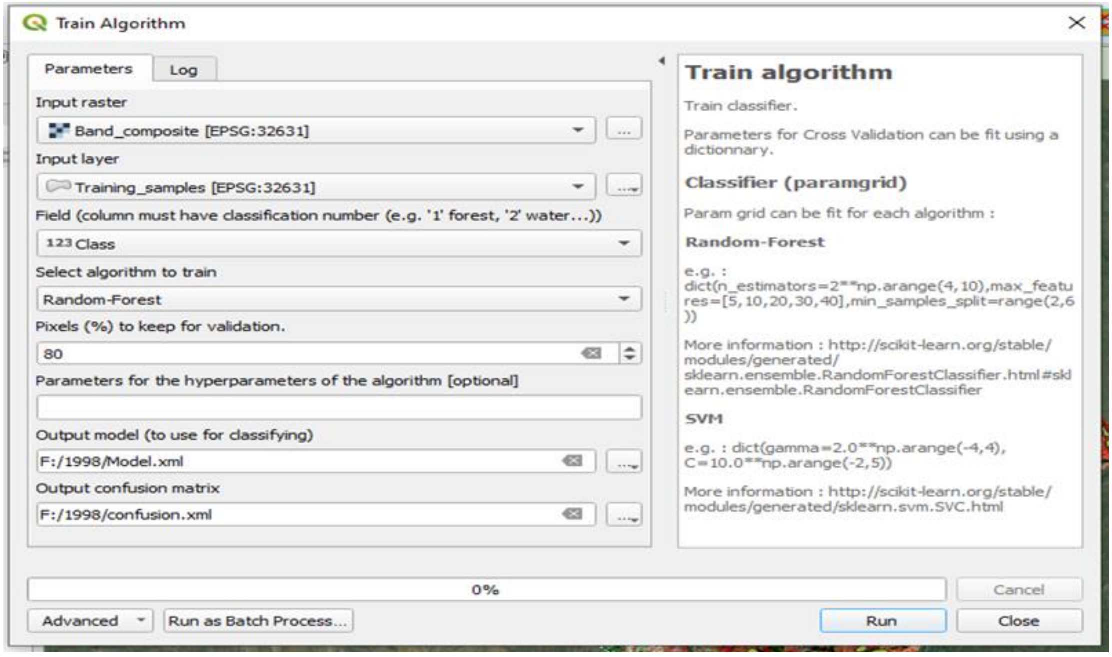

Figure 3.3 Screenshot of model training algorithm in QGIS

Between 5th November 2021 and 15th December 2021, land cover data has collected from eight villages namely (Porga, Dassari, Kani, Sepounga, Nanebou, Tchanwassaga, Sangou, and Batia). Three quadrants (30 m×30 m) were strategically placed in each land class per village, resulting in a total installation of 120 quadrats. Using a handheld Geographical Positioning System (GPS), data was collected from ten sampling points per each quadrat, accumulating a dataset of one thousand two hundred (1200) ground truth points. The X and Y coordinates were extracted from the ground truth data from the GPS and utilized Microsoft Excel software to transform it into CSV format. The resulting coordinate data was exported into QGIS and converted into a shapefile. The researchers used the collected sample points were used to establish a training site for the land cover classification 2020. The accumulated ground truth points derived from the samples into 80% for model training and 20% for validating the accuracy of the satellite-derived land cover classes (Figure 3.3).

The accuracy evaluation establishes how accurately the categorized image depicts the actual scene. It is essential to evaluate the accuracy of the classification findings since land-use maps created by image classification frequently contain inaccuracies. The researchers develop trust in the conclusions and subsequent change detection through this evaluation (Girma *et al.,* 2021). To assess the accuracy of the generated land cover maps for 2020, the remaining 20% of the field data were used for sample validation.

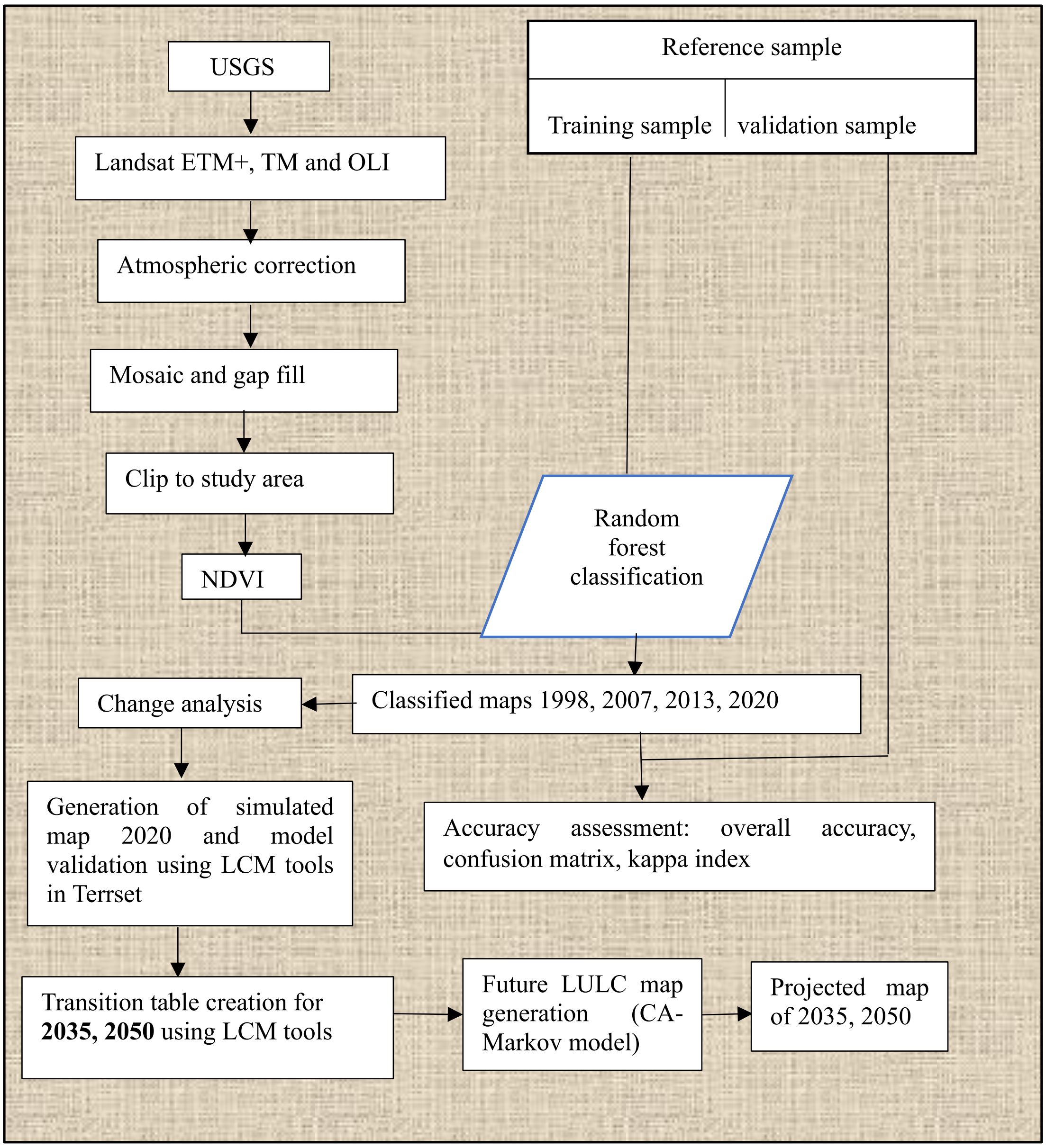

Figure 3.4 Flowchart of the steps implemented in QGIS to obtain a land cover map

Validated the Landsat-derived land cover map for 1998, 2007, and 2013 actively using a dataset from Google Earth imagery. Sample points were created from Google Earth Pro at random and uniformly spaced intervals within each land cover class to determine the confusion matrix and assess the overall classification accuracy. Additionally, the satellite-derived land cover classes' Kappa coefficient and total error were estimated.

The Normalized Difference Vegetation Index ((RED IR) / (RED + IR)) was calculated and added to the composites to improve the classification outcomes. The processes shown in Figure 3.4 were used in this study's data collection and processing for remotely sensed information. The overall accuracy (OA) and the Kappa index (K), as specified by Equations (3.1) and (3.2), were used to assess the classification accuracy (Yangouliba *et al.,* 2022) as:

$$A = \frac{\sum_1^n x}{\sum_1^n X'} \qquad [3.1]$$

where x is the number of correctly classified samples, and X is the total number of samples

$$K = \frac{N \sum_{i=1}^{r} xii - \sum_{i=1}^{r} (xi + Xx + 1)}{N^2 \sum_{i=1}^{r} (xi + Xx + 1)} \qquad [3.2]$$

where r denotes the error matrix's number of rows and columns, N is the total number of observations (pixels), xii indicates the observation in row I and column I, Xi denotes row I marginal total, and Xi denotes column I marginal total. Additionally, the LULC maps from 1998, 2007, 2013, and 2020 had their confusion matrices computed. Knowing the origins of misclassification for a LULC unit is possible, thanks to the confusion matrix (Liu *et al.*, 2020).

3.2.2.2 Change Land Use Land Cover

The Land Change Modeler (LCM) model assessed changes in land use and land cover (LULC). The main results from the LCM in this part are the quantitative evaluations of several LULC categories by each LULC. Change analysis was conducted utilizing the classified maps from 1998, 2007, 2013, and 2020 and the anticipated LULC maps for 2035 and 2050 (Leta *et al.,* 2021) to show the pattern of changes. Using the categorized photos as a starting point, numerical data were retrieved to assess the LULC dynamics across each research period. The images from related eras were crosstabulated and compared to identify the shifting pattern. A probability matrix was produced using the LCM for the intervals of 1998–2035. For the LULC categories, the change percentage was also estimated (Yangouliba *et al.,* 2022), and the change rate (Aniah *et al.,* 2019) Equations (3.3) and (3.4) was used to calculate the number of changes that occurred for various LULC categories between the periods.

$$\text{Percentage of change} = \frac{\text{Ay}-\text{Ax}}{Ax} * 100 \quad [3.3]$$

$$\text{Rate of change} = \frac{\text{Ay}-\text{Ax}}{T} \quad [3.4]$$

where Ax is the LULC area of an earlier land cover image, Ay is the LULC area (ha) of a later land cover image, and T is the time interval between Ax and Ay in years.

3.2.2.3 LULC Change prediction

3.2.2.3.1 LULC Change Prediction

The researchers used the Land Change Modeler (LCM) contained in the TerrSet Geo-spatial Monitoring and Modeling System (TGMMS) software to forecast future land use and land cover (LULC) for a given year based on classified historical satellite photos. According to Ayele *et al.,* (2019), the LCM quantifies the land cover change between earlier and later LULC by calculating the relative numbers of transitions. It also identifies the variables that would affect future LULC change. It has been put through a lot of testing and used to simulate various land cover categories, forecast change, and look at implications for biodiversity (Roy *et al.,* 2016). By considering losses and gains for each LULC category, the module adjusts the LULC assessment. The LCM produces a complex projection map and a soft projection map. A distinct land use category is assigned to each pixel on the complex projection map for the projected year (Kusiima *et al.,* 2022). The soft projection map, which gives each pixel a value between 0 and 1, signifies vulnerability. According to Gibson *et al.,* (2018), a lower number denotes a reduced exposure to change, whereas a more significant value indicates a higher susceptibility to change.

The trend in variations of land use and land cover (LULC) changes for 1998, 2007, 2013, and 2020 to predict future changes in the research area were estimated. The projected land-use changes were determined by analyzing historical data, current trends, and expected future changes. To simulate future changes over time based on past changes, the TerrSet model utilized CA-MC, a stochastic modelling technique (Fathizad et al., 2020). By employing the Transition Probability Matrix (TPM), the model forecasts the spatial arrangement of various LULC categories and situations (Wang et al., 2021).

The Bayes equation (Equation 3.2), which assesses the change by contrasting the initial (T1) and subsequent (T2) land cover conditions, is used by the Markov matrix model to predict LULC change.

S(t+1) = Pij*S(t) …... ………………………………………………………[3.5]

$$Pij=\begin{bmatrix} P11 & P12 & P1n \\ P21 & P22 & P2n \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots[3.6]$$

Pn1 Pn2 Pnn

where $0 \leq Pij < 1$ and $\sum_{j=1}^{n} Pij = 1$, (i, j = 1, 2, . . . , n). The following equation expresses the cellular automata model:

S(t,t+1) = f[s(t),N]………………………………………………………………[3.7]

Where "S(t) and S(t+1) represent the system status at two different times, t and t + 1 respectively. N denotes a cellular field, F represents the transformation rule of cellular states in local space, S represents a set of limited and discrete cellular conditions, and

Pij represents the transition probability matrix in a specific form". The CA-Markov considers limitations and other criteria to create a single map of appropriateness (Singh *et al.,* 2018). The model establishes the probability transition matrix and transition probability zones. The probability transition matrix contains the chance of a specific LULC class transitioning to another category. The pixel number anticipated to change from each LULC class during the designated period is included in the transitional region matrix.

3.2.2.3.2 Model validation

Model validation was carried out to assess the projected data's precision. The kappa coefficient was obtained and used to validate the model after simulating the 2020 land use and land cover change (LULCC) conditions using the 1998, 2007, 2013, and 2020 LULCC maps. By assessing the degree of agreement between the modeled map and the 2020 reference map using the Kappa Index of Agreement, the correctness of the generated 2020 LULCC map was evaluated.

The Kappa indices, including Kappa for no information (Kno), Kappa for location (Klocation), and Kappa for standard (K Standard) as expressed in Equations (8) to (10), were used to determine the overall success rate of the results. A Kappa coefficient (K) between 0.75 and 1 ($0.75 \leq K \leq 1.0$) indicates a high level of agreement, while a Kappa coefficient between 0.5 and 0.75 ($0.5 \leq K < 0.75$) falls within the medium agreement range. However, if the Kappa coefficient is less than 0.5 ($K < 0.5$), it indicates a low level of agreement. Once successful Kappa values were obtained, we employed the CA-Markov model to simulate the LULCC maps of 2035 and 2050. In the equations (9) and (10), the Kappa variations' summary statistics are provided per the methodology outlined by (Omar *et al.,* 2014).

$$kn_0 = \left\{\frac{M(m)N(n_1)}{P(p)} - N(n)\right. \text{ ……………………………………………… ………[3.8]}$$

$$klocation = \left\{\frac{M(m)N(n_1)}{P(p)} - N(n)\right. \text{ ……………………………………………. [3.9]}$$

$$kstandard = \left\{\frac{M(m)N(n_1)}{P(p)} - N(n)\right. \text{ ……………………………………..…[3.10]}$$

where the definitions of no information (N(n)), medium grid cell-level information (M(m)), and perfect grid cell-level information (P(p)) were used.

3.3 Results

3.3.1 Accuracy of land use and land cover classification

The classification was done on the Landsat land use and land cover change (LULCC) photos from 1998, 2007, 2013, and 2020. The outcomes of this classification are depicted in (Figure 3.2). Various metrics were employed to evaluate the accuracy of the LULCC maps developed for this period, including overall accuracy, Kappa statistics, producer accuracy, and user accuracy. The LULCC classified images for 1998, 2007, 2013, and 2020 exhibited overall Kappa statistics of 84.3 %, 85.61 %, 88.68 %, and 94.4 3%. Moreover, the researchers determined the overall accuracy for these same years to be 90.99 %, 92.15 %, 93.19 %, and 96.34 %, as presented in (Table 3.2 Major land use land cover types used and their descriptions).

Table 3.3.Accuracy assessment of land cover from 1998, 2007, 2013, and 2020.

1998	LULCC Types	Wooded savannah	Shrub savannah	Cropland	Fallow	Settlement	Row total
	Wooded savannah	41	2	3	0	0	46
	Shrub savannah	0	37	2	1	0	40
	Cropland	0	0	35	1	0	36
	Fallow	0	0	0	32	0	32
	Settlement	0	0	1	0	30	31
	Column total	41	39	41	34	30	185
	PA (%)	100	90.0	64.8	46.3	100	

UA(%)	89.1	92.5	97.2	100.	96.8	

O A= 91.00%; OK= 0.8430

2007	LU/LC types	Wooded savannah	Shrub savannah	Cropland	Fallow	Settlement	Row total
	Wooded savanah	42	3	0	0	0	45
	Shrub savannah	2	37	2	0	0	40
	Cropland	0	0	34	1	0	35
	Fallow	0	2	1	28	2	33
	Settlement	0	0	1	1	29	31
	Column total	44	42	38	30	31	185
	PA (%)	96.6	89.9	64.2	92.3	79.6	
	UA (%)	93.3	90.2	97.1	84.8	93.6	

O A= 92.16%; OK= 0.8561

2013	LU/LC types	Wooded savannah	Shrub savannah	Cropland	Fallow	Settlement	Row total
	Wooded savannah	42	2	2	0	0	46
	Shrub savannah	0	38	2	0	0	40
	Cropland	0	0	34	2	0	36
	Fallow	0	0	0	30	2	32
	Settlement	0	0	0	0	31	31
	Column total	42	40	38	32	33	185
	PA (%)	100	94.96	63.9	66.2	94.1	
	AU (%)	91.3	95	94.4	93.8	100	

O A = 93.20%; OK = 0.8868

2020	LU/LC types	Wooded savannah	Shrub savannah	Cropland	Fallow	Settlement	Row total
	Wooded savannah	44	1	0	0	0	45
	Shrub savannah	1	40	0	0	0	41
	Cropland	2	0	33	1	0	36
	Fallow	0	0	4	29	0	33
	Settlement	1	0	0	0	29	30
	Column total	48	41	37	30	29	185
	PA (%)	94.6	97.9	98.8	74.4	100	
	UA (%)	97.8	97.6	91.6	87.8	96.6	

OA= 96.34%; OK = 0.9443

UA: User's Accuracy, PA: Producer's Accuracy, K: Kappa Statistics, OA: Overall Accuracy.

3.3.2. Land use and land cover maps in 1998, 2007, 2013 and 2020

In the Riverine area of Pendjari Reserve, the dominant land use type in 1998 was Wooded savannah, covering 61.2 % of the total area. However, this Wooded savannah area experienced a decline of 4.7% between 1998 and 2007, that continued to decrease by 8 % and 11.5 % during 2007 - 2013 and 2013-2020, respectively. Shrub Savannah accounted for 27.45% of the total coverage area. The area of shrub savannah increased by 10.5 % from 1998, 2007 and 3.88 % during 2007-2013. However, there was a slight decline of 1.17 % in the shrub savannah area. Cropland constituted of the total coverage. Between 1998 and 2007, there was a decrease in cropland by 6.66 %, followed by an increase of 4.33 % and 11.1 % during 2007-2013 and 2013-2020, respectively. Fallow land decreased by 0.77 % from 1998 to 2007 but then experienced a decrease of 0.7 % and an increase of 0.83 % during 2007-2013 and 2013-2020, respectively. As for settlement, there was an apparent increase of 0.009 %, 0.5 %, and 0.28 % from 1998-2007, 2007-2013, and 2013-2020, respectively.

Table 3.4.Land use land cover change from 1998 to 2020

Years	1998		2007		2013		2020	
LULCC types	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)	Area (ha)	(%)
Wooded savannah	103,366.8	61.2	95,423.6	56.5	81,904.5	48.5	632,47.6	37.5
Shrub savannah	46,368.2	27.5	64,090.7	37.9	70,643.5	41.8	68,672.5	40.6
Cropland	17,208.5	10.2	5,963.9	3.5	13,268.2	7.9	32,029.5	19
Fallow	1,410.8	0.8	2,725.7	1.6	1,539.1	0.9	2,936.1	1.7
Settlement	538.1	0.3	688.5	0.4	1537.1	0.9	2,006.7	1.2
Total	168,892.4	100	168,892.4	100	168,892.4	100	168,892.4	100

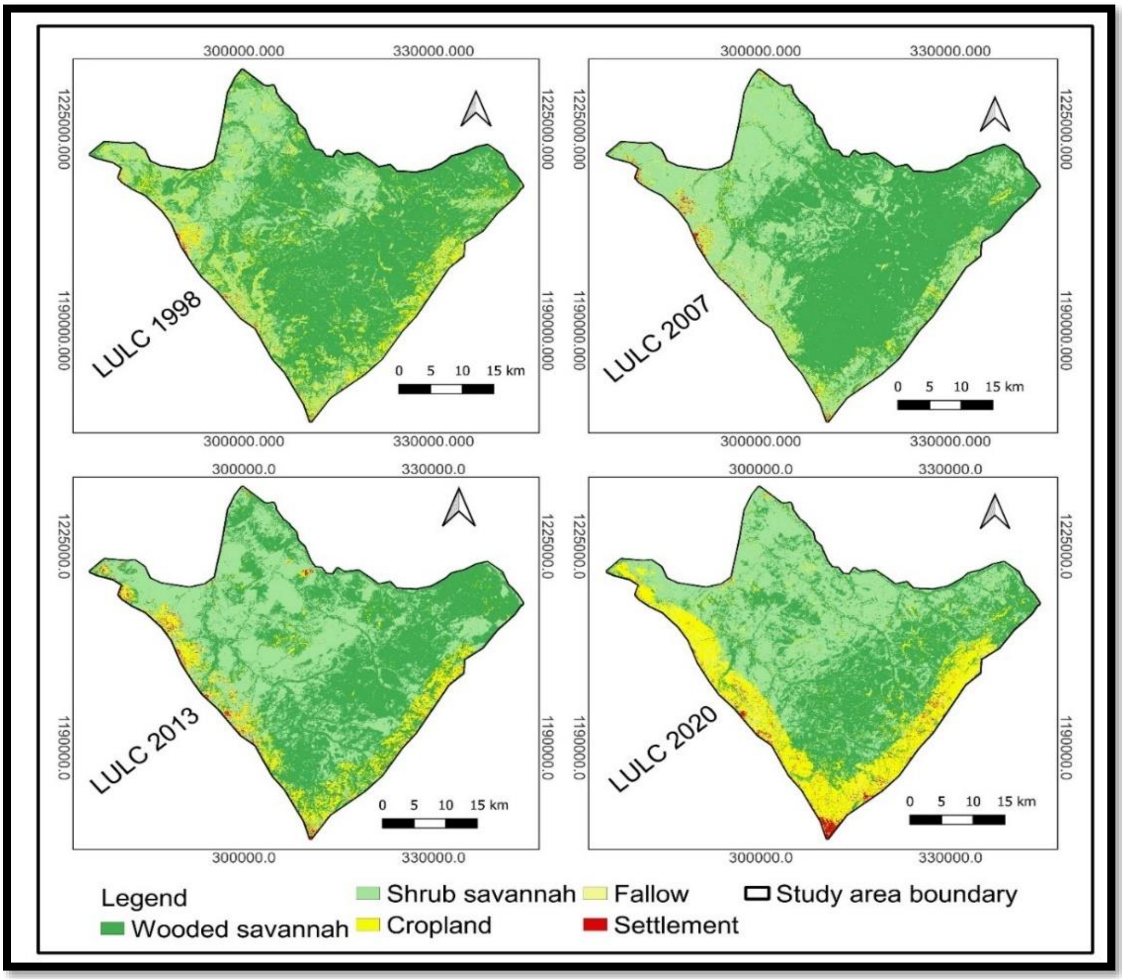

Figure 3.5.Dynamic of LULCC change in the riverine area of Pendjari reserve from 1998 to 2020

Table 3.5 .Change in land use and rate of change in the riverine area of Pendjari from 1998 -2020

Years	Land use change 1998-2007			Land use change 2007-2013			Land use change 2013-2020			Land use change 1998-2020		
LULCC	ha	%	Rate of change (Ha/year)	Ha	%	Rate of change (Ha/year)	Ha	%	Rate of change (Ha/year)	Ha	%	Rate of change (Ha/year)
Wooded savannah	-7943.2	-7.7	-882.6	-13,519.1	-14.2	-2253.2	-18,656.9	-22.8	-2,665.2	-40119.2	-38.8	-1,823.6
Shrub savannah	17,722.5	38.2	1969.2	6,552.8	10.2	1092.2	-197.0	-2.8	-89.6	22,304.3	48.1	1013.8
Cropland	-11,244.5	-65.3	-1249.4	7,304.2	122.5	1217.4	18,761.3	141.4	2,680.2	14,821.0	-131.8	673.7
Fallow	1,314.8	93.2	146.1	-1,186.6	-43.5	-197.8	1,397.0	90.8	199.6	1,525.2	108.1	69.3
Settlement	150.4	28.0	16.7	848.6	123.3	121.2	469.6	30.6	67.1	1,468.6	272.9	66.8

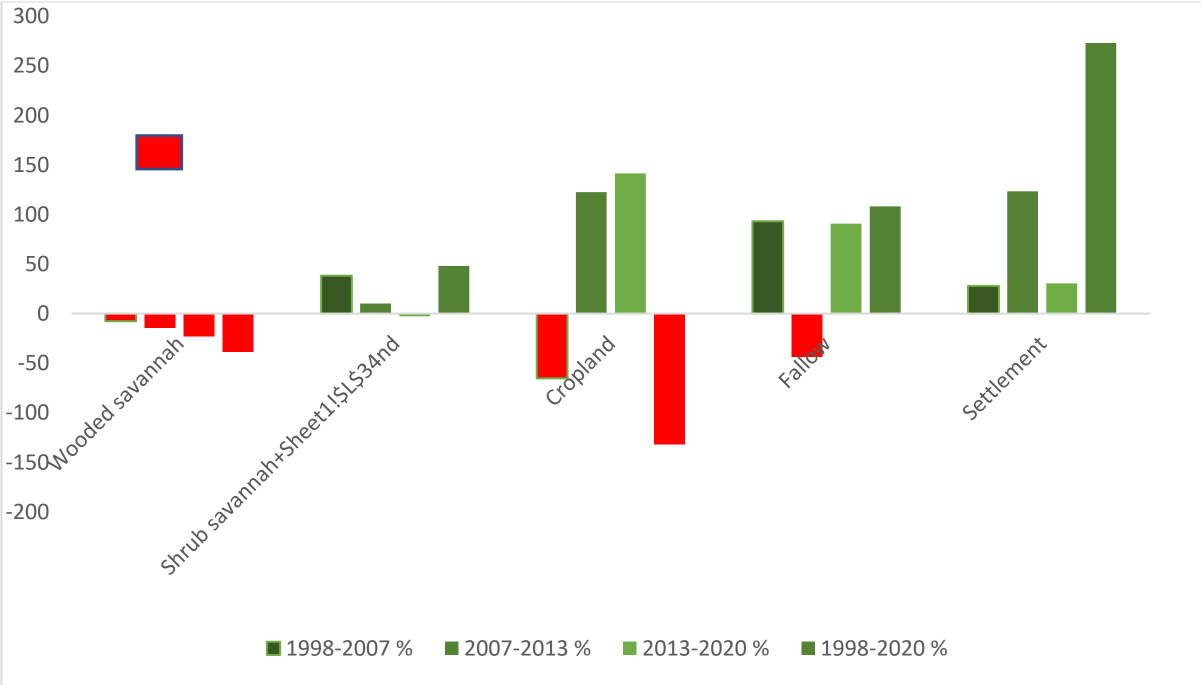

Figure 3.6.Gain and loss area of LULCC classes in 1998-2007; 2007-2013, 2013-2020, and 1998-2020

3.3.4. Validation of the model

The Validation Module measured the agreement between the two categorical maps. To evaluate the accuracy, it is essential to validate the model. Validation is a crucial step in determining the accuracy of the predicted land cover map compared to the actual map. A comparison of the actual and simulated LULC maps for 2020 was made in order to validate the projected map. The validation results represent an overview of the contrast between the simulated and actuel LULC (Table 3.6).

Table 3.6.Table 3. 6. LULCC prediction validation based on the actual and projected LULCC of 2020

Years	LULCC 2020 simulated		LULCC 2020 classified	
LULCC	ha	%	ha	%
Wooded savannah	81,905.2	48.5	63,247.6	37.45
Shrub savannah	70,657.6	41.8	68,672.5	40.66
Cropland	13,246.6	7.8	32,029.5	18.96
Fallow	1,541.6	0.9	2,936.1	1.74
Settlement	1,541.3	0.9	2,006.7	1.19
Total	168,892.4	100.0	168,892.4	100

The agreement's Kno index and the common Kappa index were used to evaluate the prediction model based on the CA-Markov model's overall accuracy. The model's location prediction accuracy was verified using the Klocation index. Table 3.7 contains the agreement indices. The average value achieved was 0.78, meaning there was a 75 % or more similarity between the LULC categories in the actuel and simulated classification. In Table 3.7, the compiled k-indices are presented. Idrisi software's validation module was used to compare the simulated and categorized maps of 2020. The Klocality index analyzed the model's ability to pinpoint suitable locations, while the Kno index assessed the model's overall accuracy. The results indicated a Kno of 0.80, a Klocality of 0.79, a KlocationStrata of 0.79, and a Kstandard of 0.72.

Table 3.7. The k-index values of the simulated LULC map of 2020

Index	P value
Kno	0.8087
Klocation	0.7944
KlocationStrata	0.7944
Kstandard	0.7274

The agreement between the two classification was measured using the Kappa index of agreement in order to shed light on the findings. Less than 0 indicates agreement that is less than chance, while a range of 0.01-0.40 denotes poor agreement. A range of 0.41-0.60 indicates moderate agreement, 0.61-0.80 denotes substantial agreement, and 0.81-1.00 denotes practically perfect agreement. These ranges are used to evaluate the

Kappa coefficient value. These statistics assessed the accuracy of the model's prediction in relation to reality while accounting for accuracy that has been corrected for chance (Mukherjee, 2009).

Using the LCM module of TerrSet 18.21 software, the agreement/disagreement component validation analysis was included of the model evaluation. Table 3.8, which further deconstructs the components into an error due to quantity/disagree quantity of 0.0494 and an error due to allocation/disagree gridcell of 0.1101. As a result, it can be effective that the CA-Markov model was effective in forecasting future LULC for the research site.

Furthermore, the data table shows that, when contrasting the simulated and actual 2020 LULC images, the main discrepancy between the two maps resulted from an allocation error rather than a quantity error. In Table 3.8, the analysis of the validation findings and the component values for agreement and disagreement are compiled.

Table 3.8:Validation result analysis (agreement/disagreement component values).

Agreement Disagreement	value	(%)
Agreement Chance	0.1667	16.67
Agreement Quantity	0.2485	24.85
Agreement Gridcell	0.4254	42.54
Disagree Gridcell	0.1101	11.01
Disagree Quantity	0.0494	4.94

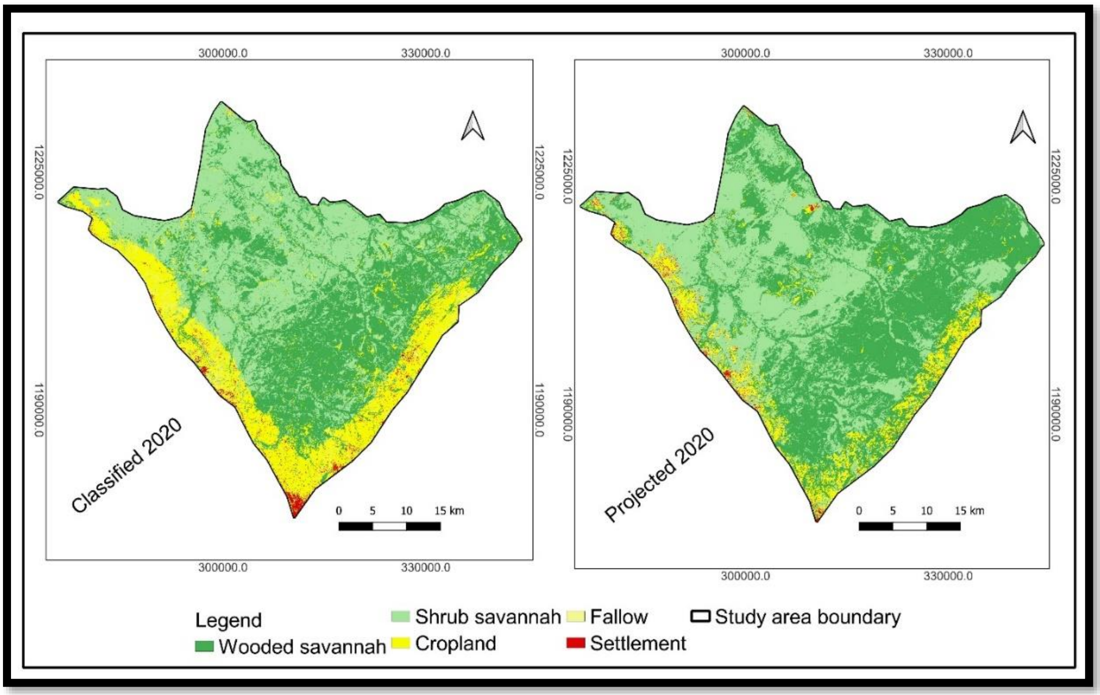

Figure 3.7: LULCC validation based on the actual and simulated LULCC of 2020

3.3.4. Future LULC dynamics

In order to align with the fifteenth goal of the Sustainable Development Goals (SDG) which focuses on conserving and restoring terrestrial ecosystems, the projections of land use and land cover change (LULCC) for 2035 and 2050 were chosen. The SDG aims to achieve this goal by 2030 (UN, 2017).

The results of the LULC projection are presented in Figure 3.7 and Tables 9 and 10. According to these results, in the riverine area of Pendjari Reserve, the fallow land is projected to increase by 35.28 hectares in 2035, with a rate of change of 2.352 hectares per year. The cropland is also expected to increase by 12.06 hectares, with a rate of change of 0.80 hectares per year. Additionally, the shrub savannah is projected to expand by 3.3 hectares, with a rate of change of 0.22 hectares per year. On the other hand, during the same period, the settlement area is anticipated to decrease by 48.96 hectares, with a rate of change of -3.26 hectares per year. Furthermore, the wooded savannah is projected to decrease by 1.71 hectares, with a rate of change of -0.114 hectares per year.

Looking ahead to 2050, the LULC projection reveals that the fallow land in the riverine area of Pendjari Reserve is expected to decrease by -1,078.1 hectares, with a rate of change of -35.94 hectares per year. Similarly, the cropland is projected to decrease by -18,299 hectares, with a rate of change of -609.96 hectares per year. In contrast, the shrub savannah is anticipated to increase by 1917 hectares, with a rate of change of 63.9 hectares per year. The settlement area is projected to decrease by -46.71 hectares, with a rate of change of -1.56 hectares per year. Additionally, the wooded savannah is expected to expand by 17,506.7 hectares, with a rate of change of 583.56 hectares per year. These projections provide insights into the potential changes in land use and land cover in the riverine area of Pendjari Reserve up to 2035 and 2050.

Table 3.9:Percentage and rate of changes in the riverine area of Pendjari from 2020-2035

	2020		2050		2020-2050		
Land use types	Area (ha)	%	Area (ha)	%	Area (ha)	Percentage of change	Rate of change
Wooded savannah	63,247.6	37.5	80,754.3	47.8	17,506.7	0.3	583.6
Shrub savannah	68,672.5	40.6	70,589.5	41.8	1,917.0	0.03	63.9
Cropland	32,029.5	19.0	13,730.6	8.1	-18,3	-0.6	-610.0
Fallow	2,936.1	1.7	1,857.9	1.1	-1,078.1	-0.4	-35.9
Settlement	1,957.7	1.2	1,957.7	1.2	-46.71	-0.02	-1.6
Total	168,892.4	100.0	168,892.4	100.0	0	0	

Table 3.10: Percentage and rate of changes in the riverine area of Pendjari from 2020-2050

	2020		**2050**		2020-2050		
Land use types	Area (ha)	%	Area (ha)	%	Area (ha)	Percentage of change	Rate of change
Wooded savannah	63,247.6	37.5	80,754.3	47.8	17,506.7	0.3	583.6
Shrub savannah	68,672.5	40.6	70,589.5	41.8	1,917.0	0.03	63.9
Cropland	32,029.5	19.0	13,730.6	8.1	-18,300.0	-0.6	-610.0
Fallow	2,936.1	1.7	1,857.9	1.1	-1,078.1	-0.4	-35.9
Settlement	1,957.7	1.2	1,957.7	1.2	-46.7	-0.02	-1.6
Total	168,892.4	100.0	168,892.4	100.0	0.0	0	

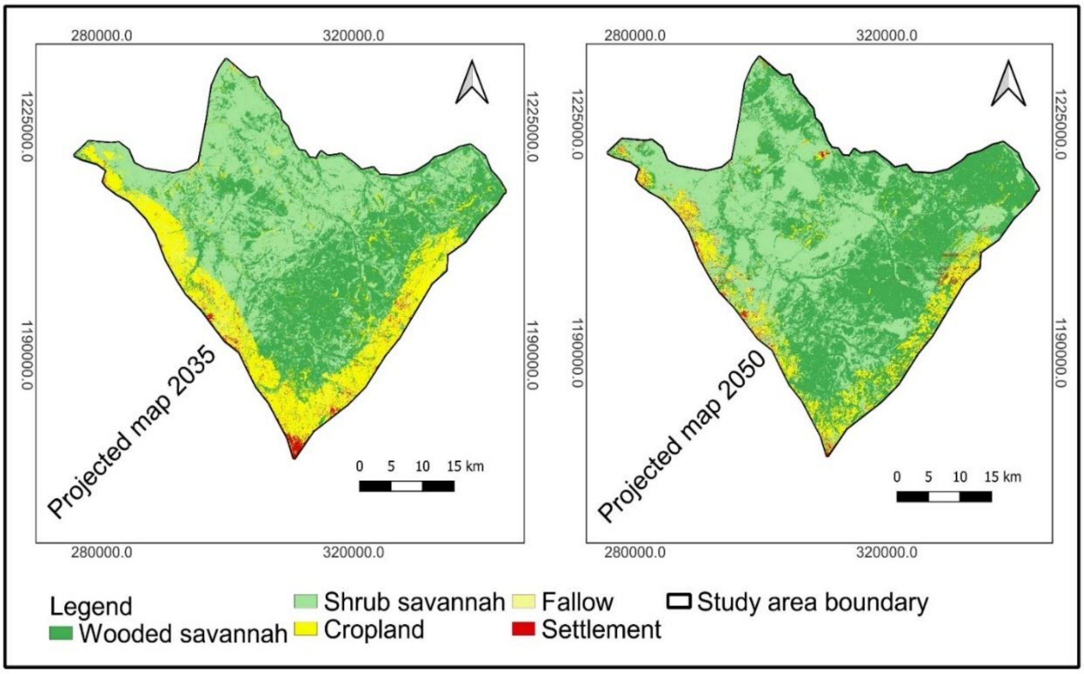

Figure 3.8:Projected LULC 2035 in the riverine area of Pendjari reserve

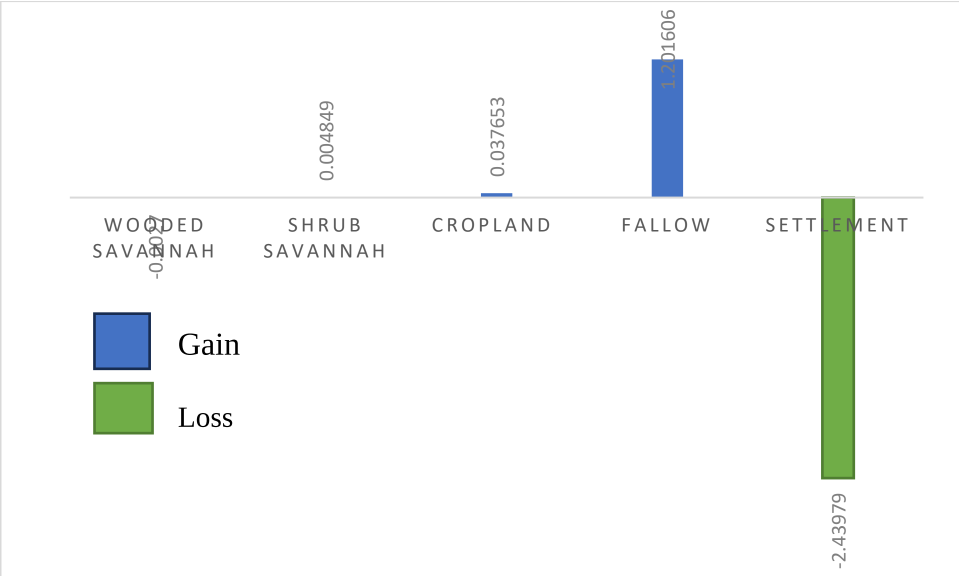

Figure 3.9: Gain and loss area of LULCC classes in 2020-2035

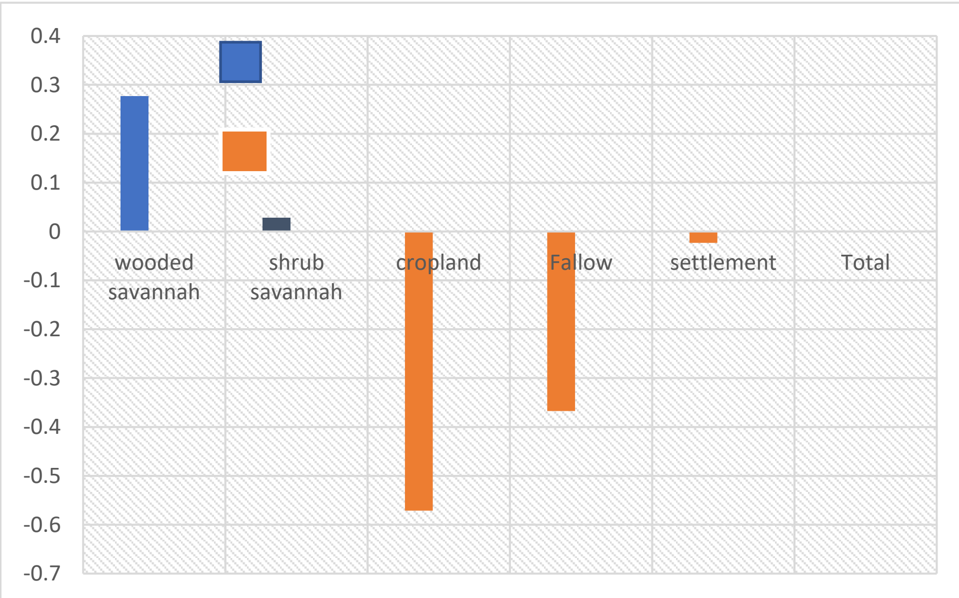

Figure 3.10: Gain and loss of LULCC classes in 2020-2050

3.4 Discussion

This study focused on analyzing the dynamics of land use and land cover change (LULCC) in the riverine area of Pendjari Reserve from 1998 to 2020 using satellite image and projecting some for 2035 and 2050. The research used five categories of Land Use and Land Cover Change (LULCC): wooded savannah, shrub savannah, cropland, fallow, and settlement, leading to the creation of four distinct maps. The analysis of overall accuracy for 1998, 2007, 2013, and 2020 indicated that the overall kappa exceeded 80 %, and the overall accuracy surpassed 90 %. These results suggest reasonably good overall accuracy and provide a reliable foundation for subsequent analysis and change detection (De Fioravante *et al.,* 2021).

Notably, the more recent LULC map accuracy results exhibited higher values, potentially attributed to the utilization of satellite images with enhanced spatial resolution. The findings revealed that the 2020 map had more misclassifications than 2013, 2007, and 1998 maps. However, the most significant confusion occurred between cropland and fallow land. This could be attributed to farmers spontaneously cultivating the land due to its environmentally friendly characteristics (Wuyun *et al.,* 2022). This finding aligns with the research by Yangouliba *et al.,* (2022), which highlighted confusion between cropland and natural vegetation classification in Burkina Faso resulting from selective trees present in croplands.

The wooded savannah and cropland were identified as the most vulnerable land cover types to land use and land cover change (LULCC) in the study area. The wooded savannah area experienced a reduction of 24.2% from 1998 to 2020, and further decline is projected by 2035. This decline in wooded savannah has potential implications for biodiversity in the Pendjari Reserve, which is renowned for its role in conserving biodiversity in West Africa. Similar findings were reported by Zhang *et al.,* (2022) in Ethiopia, where a decreasing trend in wooded savannah land was observed from 2019 to 2035. The changes in land use primarily resulted from human activities.

Based on our observations and interviews in the study area, the significant changes in the wooded savannah were linked to infrastructure development, population growth, agricultural expansion, shifting cultivation, landowner logging, encroachment for hunting and fishing, and wood harvesting for fuel. Additionally, the arrival of Mossi, Bamana, and Hasonké populations from Burkina Faso and Mali in the past decade contributed to dynamic migration patterns (Sow *et al.,* 2014).

The wooded savannah land cover alterations have also intensified conflicts between wildlife and humans. Efio *et al.,* (2022) noted that disputes between humans and nature have escalated in various African countries in recent decades due to rapid population growth and economic activities. Furthermore, the study indicated a decrease in cropland from 1998 to 2007, followed by an increase from 2007 to 2035. Overall, the changes in wooded savannah and cropland underscore the complex interactions between human activities, biodiversity conservation, and conflicts between humans and wildlife in the study area.

The decline in cropland between 1998 and 2007 can be attributed to policy decision with evection of people from their farmland. These conditions led to decreased agricultural productivity and subsequently contributed to the expansion of fallow land. Cheruto *et al.,* (2022) also noted that the growth of one land use and land cover change (LULCC) type often comes at the expense of other LULC classes. Additionally, the Atacora region, where the study area is located, experiences significant emigration, particularly among younger individuals who migrate to the Save region (Saïdou *et al.,* 2004). Push factors such as rising living costs, challenging climatic conditions, depleting natural resources, population growth, poverty, and unemployment have contributed to the high outmigration rates in the study area (Sow *et al.,* 2014).

On the other hand, the shrub savannah witnessed an increase of 15.55% from 1998 to 2020 and is projected to continue rising, indicating land degradation in the study area. These findings align with the research by Hu & Nacun (2018), which identified shrub savannah as a significant terrestrial ecosystem covering a substantial portion of China's land area and ranking as the third largest in the world. Other studies have also highlighted the fragmentation of grazing lands, resulting in higher stocking rates and increased land degradation in areas accessible to pastoralists (McLeman, 2017).

The fallow land experienced an initial increase from 1998 to 2007 and 2013 to 2020 but decreased from 2007 to 2013. The reduction in fallow land can be attributed to the population growth resulting from immigration from Burkina Faso and Mali in the past decade due to political instability and crisis, particularly in the Sahel region (generally in these two countries specifically).

The LULCC projection revealed an apparent decrease of 1.71 hectares in wooded savannah land from 2020 to 2035. According to the predictions, if the degradation continues, the settlement class will experience the most significant net loss in the study area. The slight decline in wooded savannah land from 2020 to 2035 can be attributed to the implementation of a policy to preserve the hunting zone, which involves relocating farmers from the area. The projection for wooded savannah land in 2050 could be associated with a decline in the rural population and more vigorous government enforcement of deforestation regulations and management policies.

In recent years, African Parks have taken significant steps to control deforestation and enhance surveillance in rural areas through real-time monitoring, rural patrols, and imposing substantial fines. The effectiveness of public policies in reducing deforestation has been recognized as a critical factor in protecting the study area (Janssens *et al.,* 2022). The rural population is expected to decrease significantly by 46.71 hectares between 2020 and 2050. This finding aligns with the research by Souza *et al.,* (2020), who reported a 50% decrease in the rural population in Brazil between

1986 and 2015 due to the large-scale migration of family farmers to urban centers in search of better job opportunities and improved living conditions.

This management approach may contribute to land abandonment (Atsri *et al.,* 2020). As a result, 48 hectares of settlement land would be converted into cropland, serving as a vital source of livelihood. Changes influence the conversion of settlements into agricultural areas in management and policies. Extensive agricultural policy approaches have been found to have a significant impact on wooded savannahs, as confirmed by several studies (Oestreicher *et al.,* 2014). Unfortunately, cropland, fallow land, and shrub savannah experienced an increase. It is important to note that these results should be considered general information due to the complex nature of the drivers (population increasing, agriculture and climate change) be hind LULCC.

3.5 Conclusions

The present study employed digital image processing techniques to assess change detection and land use land cover change (LULCC). Four historical LULC maps from 1998, 2007, 2013, and 2020 were generated, and future maps for 2035 and 2050 were created to analyze the trends of LULCC. The findings revealed a continuous decrease in wooded savannah land from 1998 to 2020, accompanied by significant increases in cropland, fallow, shrub savannah, and settlement areas. The conversion of wooded savannahs to settlements due to population growth had a detrimental impact on environmental degradation. The projected results indicated a slight reduction in the wooded savannah area, with a more substantial decrease observed in settlement areas.

CHAPTER 4:FARMERS' PREFERENCE FOR TREE AND CROP ASSOCIATION IN AGROFORESTRY SYSTEMS AS ADAPTATION STRATEGY TO CLIMATE CHANGE

Abstract

Agriculture remains the primary source of livelihood for the West African rural populace, but the sector is confronted with challenges related to climate change. In the Pendjari Biosphere Reserve, Benin, this study evaluated farmers' choice for tree and crop association as a climate change adaptation approach. Data were collected in two districts, Tanguieta and Materi, from 361 farmers on households' socio-demographic characteristics and benefits of the tree using a semi-structured interview guide. In contrast, the trees on farmlands were inventoried. Farm size, landholding, and District effects on tree diversity, tree species richness, tree abundance, and their interactive effects were analyzed by a General Linear Model (GLM) using R statistical software. To assess farmers' preferences, hierarchical classification was performed with factorial analysis of mixed data. The results showed that the mean of tree species diameter at breast height (*dbh*) and height ranged between 20.32 - 36.01 cm) and 6.92 - 9.74 m, respectively. *Parkia biglobosa* obtained the highest mean *dbh* (Tanguieta 36.01±2.9 cm; Materi-32.18±2.98 cm) and height (Tanguieta 8.0±0.74 m; Materi 9.0 ±1.1 m), but *Vitellaria paradoxa* had the highest height in both Districts. The most important crops were *Gossipium hirsutum* and *Zea mays*. Tree importances were the essential criteria in selecting trees for the agroforestry systems with provisioning, followed by supporting services as the most common ecosystem benefit derived by local communities. Tree-crop associations varied among the farmers. Some Farmer Groups prefered *Afzelia Africana, Leptadernia hastata, Diospyros mespiliformis, Leptadernia*

hastata, Dichrostachys cinera with *Zea mays* and *Glycine max*, *Zea mays* with *Vigna unguiculata* and *Oryza sativa*. Whereas others associated *Balanites aegyptiaca, Combretum aculeatum, Balanites aegyptica*, *Trichilia emetica, Pseudocedrela kotschyi* with *Zea mays* and *Glycine max*, and *Sesamum indicum* with *Vigna unguiculata*

Keywords: Sustainable agriculture, farmers' practices, Ecosystem services, and intercropping system.

3.2.. Introduction

In Sub-Saharan Africa, agriculture is still the primary source of income for rural households. It is critical to economic growth and contributes considerably to Sub-Saharan African countries' Gross Domestic Product (GDP). Population expansion, on the other hand, is accompanied by land degradation (Tscharntke *et al.,* 2012). Farmers generally practice shifting cultivation whereby they shift to the virgin forests when yield decrease is experienced due to soil nutrient depletion, resulting in deforestation. Improving agricultural output through extension is no longer feasible due the need for stability in providing ecosystem services (Hardaker *et al.,* 2022). Aside declining soil fertility and land degradation, climate change pocesses the most danger to agriculture and the sustainability of rural families' livelihoods in West Africa, with possible adverse effects on crop output and food security (Belew *et al.,* 2022).

Natural catastrophes have kept the West African people in chronic food insecurity for decades (Atanga & Tankpa, 2021). Food and energy scarcity has compelled people to fell trees even on sloping led, resulting in substantial deforestation and forest degradation, which has resulted in soil erosion and the loss of biodiversity and livelihood options (Asuoha *et al.,* 2019). To address this issue, a new tree-planting strategy has been devised to promote reforestation by planting the most beneficial tree species. The selection procedure, on the other hand, has received little attention. Species are selected based on economic or environmental benefits, resulting in a concentration on fast-growing wood species (Sacande & Berrahmouni, 2016).

A lot of research has demonstrated the value of trees in agroforestry systems (Belew *et al.,* 2022). The incorporation of trees into agricultural landscapes is being pushed to reduce deforestation and land degradation while improving agricultural sustainability in poor nations (Bensel, 2008). The predicament is particularly relevant in Benin, a Sub-Saharan country where low-income individuals heavily rely on agriculture and natural resources to mitigate the consequences of increased production, marketing, and adverse effects of climate change (Jost *et al.,* 2016). Because it stores atmospheric carbon dioxide (CO_2) over extended periods, integrating trees into agricultural landscapes can offer a feasible chance to address climate change challenges (Lorenz & Lal, 2014). Therefore, it should be thought of as a way to lessen the effects of climate change to have woody vegetation and crops coexist on the same piece of land as part of climate-smart multifunctional land-use systems (Bett *et al.,* 2017). To prevent croplands in China by eroded, trees and bushes have been employed as windbreakers (Gao *et al.,* 2017). Increased agroforestry adoption has been shown to offer scientific benefits in several studies. In contrast, Kuyah *et al.,* (2016) observed that farms with trees had higher soil water content than those without them. Daba (2016) reported that the moringa tree absorbs 50 times more carbon dioxide ($CO^{2)}$, than the Japanese cedar tree and 20 times more than wild flora. In Kenya, trees have been shown to enhance infiltration rate, decrease soil evaporation, and increase transpiration (Prasannakumar *et al.,* 2012).

According to research conducted in Benin, trees in agroforestry systems offer a variety of benefits to the farmstead, including shade, shelter, food, fodder, and many other commodities and services (Gnonlonfoun *et al.,* 2019). Therefore, agroforestry systems have the best chances to address climate change challenges since they have the capacity to store atmospheric CO^2 for a long period of time (Lorenz & Lal, 2014). Other known benefits of agroforestry systems include environmental functions (Castle *et al.,* 2022) with biodiversity conservation (Ouinsavi & Sokpon, 2008), regulation of fluxes in ecosystems, and mitigation of pollution (Gbedomon *et al.,* 2017).

According to (Fandohan *et al.,* 2010), smallholder farmers are known ledgeable various ecosystem services, including those offered by tree and agroforestry systems (Paudel & Shrestha, 2022). Despite these advantages, challanges must be resolved before tree-based farming can be adopted and sustained. Farmers seldom use local environmental knowledge when selectif and planting trees because of their limited resources, making it difficult to find species that can satisfy socio-ecological demands (Yasin *et al.,* 2021). The foundation of the agroforestry system is the selection of desirable tree species. The indigenous parkland farming method comprises alternating cycles of agriculture and fallows in which the natural regeneration of woody plants occurs around conserved trees, such as shea trees (*Vitellaria paradoxa*). As a result, tree species beneficial to the local population dominate phytodiversity in parklands and old fallows. This study is to (i) assess tree diversity in agroforestry systems and (ii) evaluate farmers' criteria for selecting preferred trees on their farms.

4.2.Methods

4.2.1. Site characteristics

The research was carried out in the Pendjari Biosphere Reserve's riverine area, located in the northwestern part of the Republic of Benin (10.30 to 11.30 ºN; 0.50 to 2.00 ºE). The research was conducted in two zones: the Zone of Controlled Occupation, which allows settlements and all agricultural operations, and the Hunting Zone, which allows medium-impact activities. The climate in this Sudan area habitat is defined by a dry season from October to May and a wet season from June to September, with annual rainfall ranging from 800 to 1000 mm. Open grass and tree savannahs, intermingled with dry and gallery forests, make up the vegetation. This area is home to several wildlife species, especially large carnivores (Sogbohossou *et al.,* 2014). The mean annual is 27°C temperature. The primary highways through the Reserve are Tanguieta Porga and Tanguieta Batia. The three largest ethnic groups in the nation are Berba, Gourmantche, and Wama. Most communities are populated by Fulani pastoralists in addition to the native farmers with each town have one to eight camps.

4.2.2. Sampling procedures and data collection

Following a pre-survey of all agroforestry sites, a random sample (West, 2016) was utilized to choose pilot sites based on community distribution. The snowball purposive sampling was used to select farmers from each pilot location. The research focused on the major communities of Berba, Gourmantche, and Wama, forming 55 %, 35 %, and 10 % of the entire study region, respectively. The proportionality technique was used to pick eight sites: four in Berba communities (Porga, Dassari, Kani, and Sepounga), two in Gourmantche communities (Sangou and Batia), and two (Tchanwassaga and Nanebou) in mixed communities areas Gourmantche and Wama Using the Normal approximation of the Binomial distribution (Dagnelie *et al.,* 1998), the sampling size n was determined using Equation 4.1.

$$n = \frac{p_i(1-p_i)U^2_{1-\alpha/2}}{d^2} \qquad [1]$$

where *n* is the estimated sample size for the research area, $U^2_{1-\alpha/2}$ is the value of the normal random variable (1.96 for =0.05), and d is the estimation's margin of error, which was set at 5 % to allow for the sampling of more farmers and a wider range of local residents' perspectives. Three hundred and sixty-one (361) farmers were randomly selected for the assessment of tree and crop species in the agroforestry system. The key factor in farmer selection was the tree cover on the farmland of the farmer. A semi-structured interview questionnaire was used to solicit data on tree and crop species from the farmers. In addition, the tree and crop species on each farm were inventorised. The tree species were identified with the help of experts who knew the names of the trees in the local language. The taxonomic identification of the tree species was based on the analytical flora of Benin (Akouègninou *et al.,* 2006). Species not immediately recognized in the field were later identified in the National Herbarium of the Faculty of Science and Technology of the University of Abomey-Calavi.

The identification process involved identifying the scientific name and the family of each tree. Complementary sources for conservation status included the West Africa Biodiversity Atlas (Sinsin & Kampmann, 2010), the IUCN online database (Trull *et al.,* 2018), the Benin Red List of Threatened Plant Species (Neuenschwander & Adomou, 2017) and the online database of The Plant Resources of Tropical Africa (Castle *et al.,* 2022). The field observation approach was used to identify types, cropping systems, management, and yield of crops on the agroforestry farmlands and varietal diversity cropping system. A standard pre-tested structured questionnaire collected information on home characteristics, occupational characteristics, tree species growing on the farms, and their purposes. To better understand the different cropping systems, a questionnaire was used to assess farmers' knowledge of crop management systems (monoculture or intercropping), trees (cultivated and wild crops), current cropping systems, and intent to introduce different cropping systems. To ensure that the questions were clear, the questionnaire was pre-tested with 10 farmers (who did not participate in this study). To ensure that the participants understood the Likert scale, the response scale was defined using an example before each interview.

The study utilized a questionnaire consisting of five sections to gather qualitative data. These sections covered various aspects including: (i) the presence of trees and agricultural land use on farms, as perceived by farmers; (ii) the motivations and factors that influence farmers' decisions to integrate trees into their farming practices; (iii) questions related to the environment and attitudes towards tree integration; (iv) the ecosystem services provided by on-farm trees within agroforestry systems; and (v) socio-demographic information of the farmers. The questionnaire was administered through a household survey conducted in the local language, both in the morning and evening, at the participants' homes. Socio-economic factors such as household size, landholding size, ethnic group, age, gender, and education level were collected. The interviews were conducted with the head of the household, regardless of gender, as long as they were above the age of 30. To ensure accurate recording of the services identified by each group, a facilitator provided feedback and participants were encouraged to express their agreement or disagreement regarding the ecosystem services mentioned. Once consensus was reached on the identified services, participants were asked to rate the importance of each service (referred to as "perception") on a scale of 1 to 4, with 1 indicating low importance and 4 indicating high importance. Additionally, participants were asked about the trends of these identified ecosystem services over the past 30 years. The survey aimed to understand farmers' perceptions of tree species in agroforestry as strategies for climate change adaptation.

Tree structural traits, ecosystem services, and diversity were evaluated using an integrated approach (i.e., a combination of qualitative and quantitative methodologies). Quantitative information was measured for each farm, including tree height (H) and diameter at breast height (*dbh*), which are dendrometric dimensions. A clinometer was used to measure tree height and a diameter tape to gauge the dbh of several tree species on the selected farms were used to gather densitometric data. Using the GPS receiver (Garmin 76CSx), the size of each participating farmer's farmland was calculated.

To examine the preferences of farmers for tree crop association in agroforestry, the number of services derived from each tree selected in an agroforestry system was listed according to ethnicity group, and the cropping systems that were related were also recorded.

4.2.3. Data analysis

Descriptive statistics were used to examine the acquired data, including percentages, tables, and graphs. The socio-demographic attribute (Ethnicity, Age, Gender, and Education level) of the farmers in each district was evaluated by their relative frequencies. The age of the respondents was classified into less than 30 years (< 30 years), between 30 and 60 years (30 – 60 years),, and above 60 years (> 60 years) as young, adult,, and old, respectively (Minicuci *et al.,* 2014). Microsoft Excel was used to examine the total number of crops in the agroforestry system and the percentage of each crop.

Taxonomic diversity and observed species richness, diversity indices (Shannon and Simpson), and associated data were developed for each studied district. Taxonomic diversity considers the number of species, genera, and families. The Shannon diversity index (*H)* was used to analyze the diversity of woody species as a measure of species abundance and richness. This index takes into account both species abundance and species richness (Equation 4.2):

$$H = -\sum_{k=1}^{S} \text{pi} \ln pi' \qquad [4.2]$$

where s is the number of species and pi is the ratio of individuals of species i to the total number of individuals of all species N.

The Simpson's diversity index (D), which assesses community diversity, was used to assess biodiversity. It can also evaluate population diversity variations in plant communities and other environments. The power of the index resides in its capacity to calculate and compare two sets of data to ascertain which is more diversified. The range is 0 to 1, with high scores (almost 1) denoting high diversity and low scores (nearly 0) characterizing low diversity. The formula for the index is Equation 4.3:

$$\mathrm{D} = 1 - \frac{\Sigma \mathrm{n}(\mathrm{n}-1)}{\mathrm{N}(\mathrm{N}-1)} \qquad [4.3]$$

Where: n is the number of individuals of each species and N is the total number of individuals of all species. Further, a linear model was used to test the effect of the farm area, landholding and district on the tree diversity, richness and generalized linear model on species abundance.

The ideal model for the tree species diversity indices was chosen using the Akaike information criterion (AIC). A mathematical technique for assessing how well a model matches the data it was developed from is the AIC. The best-fit model, according to AIC, is the one that explains the most variation with the fewest number of independent variables. It is used to assess various potential models and determine which is best suited for the data.

To describe preferences of communities to tree species, hierarchical classification (Ward, 1963) with factorial of mixed data was performed using the FactoMineR of the R software package (Lê *et al.,* 2008). To describe each homogeneous class through the most discriminant variables, the v-test statistics was computed (Josse & Husson, 2016). The most discriminant variables of each were those for which the absolute value of v-test was greater than 2. All the statistical analyses were performed with the *R* software package (Version 4.1).

4.3.Results

4.3.1. Socio-demographic characteristics of households

From a total of 361 households interviewed in this study, the dominant ethnic group was Berba (49.86 %), followed by Gourmantche (45.15 %), while Wama was the least (4.98 %) (Table 4.1). Males constituted 82.0 7% as heads of households, while females constituted only 17.93 %. From the total respondents of age range,14.65 % of households were young, 79.31 were adults, and 6.04 % were old. For the education level, 53.46 % of households had no formal education, 34.90 % were up to primary school, 11.35 % were up to secondary school, and 0.35 % had obtained tertiary level education. The average farm size in the study area was 1.19±0.33ha-1. Concerning ownership of land in possession, 32.40 % of households were landowners, while 67.59 % of households were tenants.

Table 4.1.Socio-demographic characteristics of households in the two studied districts

Variables	Levels	Materi (%)	Tanguieta (%)
Ethnic group	Berba	73 (100)	107 (37.15)
	Gourmantche	0	163 (56.6)
	Wama	0	18 (6.25)
Age group	Young	12 (16.44)	37 (12.85)
	Adult	57 (78.08)	232 (80.56)
	Older	4 (5.48)	19 (6.6)
Education level	Informal	33 (45.21)	160 (55.56)
	Primary	29 (39.73)	97 (55.56)
	Secondary	11 (15.07)	30 (10.42)
	Tertiary	0	1 (0.35)
Gender	F	14 (19.18)	48 (16.67)
	M	59 (80.82)	240 (83.33)
Landholding	Yes	26 (35.62)	91 (31.60)
	No	47 (64.38)	197 (68.40)
Average farm size (ha)		1.18 (47.66)	1.20 (62.15)

4.3.2 Inventory of tree and crop species in the agroforestry systems

4.3.2.1. Crops cultivated in the agroforestry systems

A total of 10 different crops were grown on the sampled parcels of croplands. The most important crops were upland cotton (*Gossipium hirsutum*) and maize (*Zea mays*), constituting 31.23 % and 27.12 % of the total surveyed area. Other crops of medium importance: sorghum (*Sorghum bicolor*) and millet *(Panicum miliaceum)*, sesame (*Sesamum indicum*), rice (*oryza sativa*) cowpea (*Vigna unguiculata*) and soybean (*Glycine max*) forming 11.92%, 11.46%, 5.4 %, 4.92 % and 3.86 % of the surveyed area, respectively. The remaining minor crops noted in farming systems are groundnuts/peanuts (*Arachis hypogea*), bambara groundnuts (*Vigna subterranea*), pigeon pea (*Cajanus cajan*) forming 2.1 %, 1.2 %, 0.79 %, respectively. Some crops association observed were: maize (*Zea mays*) and cowpea (*Vigna unguiculata*); cotton (*Gossipium hirsutum*) *and* cowpea (*Vigna unguiculata*); *Sesame (Sesamum indicum)* and cowpea *(Vigna unguiculata); sesame (Sesamum indicum)* and maize *(Zea mays),* sorghum *(Sorghum bicolor) and sesame (Sesamum indicum), sorghum (Sorghum* *bicolor) and cowpea (Vigna unguiculata)* and *sesame (Sesamum indicum) and* pigeon pea *(Cajanus cajan*)

4.3.2.2. Tree species inventoried in the agroforestry systems

A total of 38 tree species belonging to 19 families were enumerated in the farmlands of the study area (Table 4.2). Among the families, Fabaceae was the family with the most diverse species (12), followed by Moraceae (4) (Table 3). The indigenous trees were more represented (84.21 %) than exotic ones. For conservation status, 47.36 % of trees were Least Concerned (LC), 39.47 % were Not Evaluated (NE), 7.89 % were Vulnerable (VU), and 2.64% respectively were Near Threatened (NT) and Endangered (EN).

Table 4.2. Tree species inventoried in the agroforestry systems, Pendjari Biosphere Reserve

Number	Scientific name	Family	Services	Indigenous (I)	Exotic (E)	Conservation status
1	*Acacia macrostachya*	Fabaceae	Food, medicinal	I		LC
2	*Acacia auriculiformis*	Fabaceae	Timber, energy		E	LC
3	*Adansoni digitata*	Bombacaceae	Food, medicinal,	I		NE
4	*Afzelia Africana*	Fabaceae	Timber, energy	I		VU
5	*Anarcadium occidentale*	Anacardiaceae	Food, energy		E	NE
6	*Anogeissus leiocarpa*	Combretaceae	Timber	I		LC
7 8	*Azadirachta indica*	Meliaceae	Food, medicinal, energy		E	NE
9	*Balanites aegyptiaca*	Zygophyllaceae	Food, medicinal	I		NE
10	*Bombax constatum*	Malvaceae	Food, medicinal	I		NE
11	*Burkea Africana*	Fabaceae	Timber, energy	I		LC
12	*Combretum aculeatum*	Combretaceae	Medicinal, energy	I		LC

13	*Combretum collinum*	Combretaceae	Medicinal, energy	I		LC
14	*Daniellia oliveri*	Fabaceae	Medicinal, energy, beehive	I		LC
15	*Dichrostachys cinerea*	Fabaceae	medicinal	I		LC
16	*Diospros mespiliformis*	Ebenaceae	Timber, food	I		NE
17	*Erythrina senegalensis*	Fabaceae,	Energy	I		LC
17	*Eucalyptus camadulensis*	Myrtaceae	Energy, timber		E	NE
18	*Ficus glumosa*	Moraceae	Fodder, energy	I		LC
19	*Ficus platyphylla*	Moraceae,	Food, medicinal	I		LC
20	*Ficus vallis-choudae*	Moraceae,	food, medicinal	I		NE
21	*Gmelina arborea*	Verbenaceae	Energy, soil protection		E	NE
22	*Gymnosporia senegalensis*	Celastraceae	Energy, fodder	I		LC
23	*Khaya senegalensis*	Meliaceae,	Timber, medicinal	I		VU
24	*Lannea microcarpa*	Anacardiaceae ,	Food, fodder, energy	I		LC
25	*Leptadernia hastata*	Apocynaceae	Medicinal, fodder	I		NE
26	*Lonchocarpus laxiflorus*	Fabaceae	Medicinal, energy	I		NE
27 *28*	*Mangifera indica*	Anacardiaceae	Food, medicinal, energy		E	NE
29	*Milicia excelsa*	Moraceae	Soil fertility, timber energy	I		NT
30	*Parinari congensis*	Chrysobalanaceae	Food, timber, energy, fodder	I		LC
31	*Parkia biglobosa*	Fabaceae	Timber, medicinal, food	I		LC
31	*Prosopis Africana*	Fabaceae	Fodder, timber, energy	I		NE

32	*Pseudocedrela kotschyi*	Meliaceae	Medicinal, energy	I		LC
33	*Pterocarpus erinaceus*	Fabaceae	Food, timber, energy	I		EN
34	*Sarcocephalus latifolus*	Rubiaceae	Medicinal	I		NE
35	*Tamarindus indica*	Fabaceae	Food, energy	I		LC
36	*Trichilia emetica*	Meliaceae	Energy, medicinal	I		LC
37	*Vitellaria paradoxa*	Sapotaceae	Food, fodder, energy	I		VU
38	*Vitex doniana*	Lamiaceae	Food, energy	I		NE

4.3.3. Identification of common tree species and their important ecosystem services

4.3.3.1. Population structure of tree species in the agroforestry systems

To evaluate the tree species structural characteristics of ecosystem services provided by different tree species, it is necessary to investigate their structural characteristics. The three most important tree species are *Vitellaria paradoxa, Parkia biglobosa* and *Lannea macrocarpa*.

Results of analysis of variance (ANOVA) of the dendrometric parameters (*dbh* and height) of agroforestry tree species is presented in Table 4.3. Tree height varied significantly among the studied districts (p = 0.000), tree species (p = 0.014) and interaction between the districts and tree species (p = 0.021). Diameter (*dbh*) only varied significantly among the tree species (p = 0.000). As presented in Figure 3, The mean *dbh* ranged between 20.32 ± 1.89 cm and 36.01 ± 2.9 cm in Tanguieta and between 26.26 ± 3.2cm and 32.18 ± 2.98 cm in Materi. *P. biglobosa* had the highest mean *dbh* in both districts with mean *dbh* of 36.01 ±2.9 cm in Tanguieta and 32.18 ± 2.98 cm in Materi. However, the mean *dbh* values of *L. macrocarpa* (26.26 ± 3.25cm) and *Vitellaria paradoxa* (29.27 ± 1.0 cm) in Materi were higher than the species mean *dbh* values observed in Tanguieta (20.32 ± 1.89 cm and 28.22± 0.51cm, respectively). Apart from *L. macrocarpa*, the lowest mean height was observed in Tanguieta (6.92±0.44 m) and the highest mean height was observed in Materi district (7.75±1.01 m). About 50% of population of *Lannea macrocarpa, P. biglobosa* and *V. paradoxa* had *dbh* of 28.65 cm, 34.06 cm and 28.01 cm, respectively in Materi. However, in Tanguieta, 50% of population of *L. macrocarpa, P. biglobosa* and *V. paradoxa* had diameters of 16.71 cm, 31.51 cm and 26.42 cm, respectively.

Effects of district and tree species (P. biglobosa, V. paradoxa and Lannea microcarpa) of structural parameters

Table 4. 3: Effects of district and tree species (*Parkia biglobosa*, *Vitellaria. paradoxa* and *Lannea microcarpa*) of structural parameters

Source of variation	Diameter *(dbh)*		Height	
	F value	Pr(>F)	F value	Pr(>F)
District	3.42	0.065	42.73	0.000
Tree species	19.63	0.000	4.35	0.014
District x Tree species	2.96	0.053	3.89	0.021

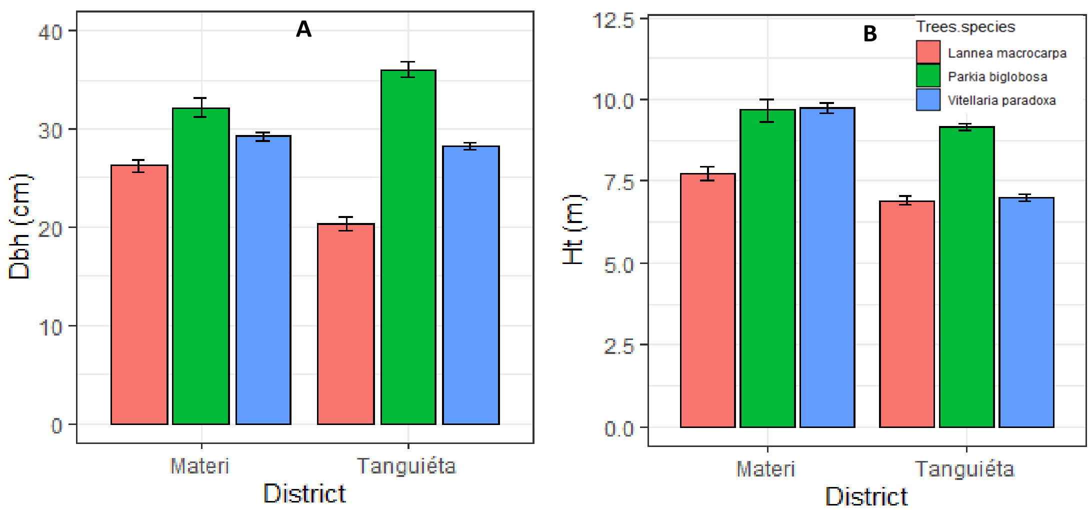

Figure 4.1.A) Diameter (dbh) and (B) height of tree species enumerated in agroforestry farmlands from the two studied districts (Materi and Tanguieta

Table 4.3.Structural characteristics of tree species enumerated in agroforestry farmlands from the two studied districts.

District	Tree species	Diameter (*DBH*)				Height			
		Me	Se	Med	Ske	Me	Se	Med	Ske
Materi	*L. microcarpa*	26.26	3.25	28.65	-0.34	7.75	1.01	7.5	0.11
	P. biglobosa	32.18	2.98	34.06	-0.41	9.67	1.19	8	0.85
	V. paradoxa	29.27	1	28.01	0.85	9.74	0.36	9	1.1
Tanguieta	*L. microcarpa*	20.32	1.89	16.71	0.72	6.92	0.44	6.5	1.44
	P. biglobosa	36.01	2.9	31.51	1.6	9.14	0.42	8	0.74
	V. paradoxa	28.22	0.51	26.42	0.73	6.98	0.15	7	1.04

Me: mean; Se: standard deviation; Med: median; Ske: Skewness

4.3.3.2. Ecosystem services derived from tree in agroforestry systems

The criteria of tree selection in agroforestry including particular tree species were supported by many reasons specific to farmers. Four main services were derived from the tree on farmlands by the local community members (Figure 4.3). This was followed in a decreasing order by regulatory ecosystem service with the proportion being 17.1% and 14.4 %, and supporting function with the proportion being 15.9 % and 4.3 %, and with the least Cultural benefits with the proportion of 8.67 % and 3.6 % for Tanguieta and Materi Districts, respectively.

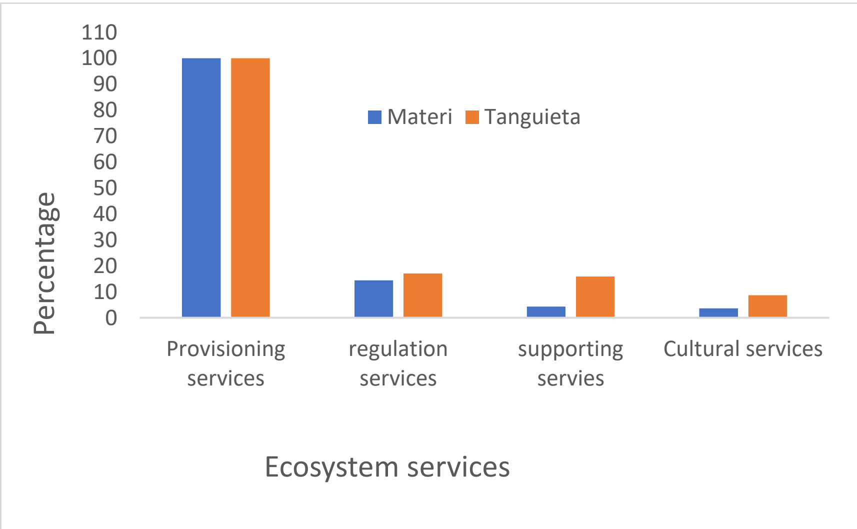

Figure 4.2.Important ecosystem services used by famers for tree selection

4.3.3.3. Determination of tree diversity indices in agroforestry systems

The best model for the tree species abundance (AIC=2427.97) and the tree species richness (AIC=1352.70) was the additive model, while the multiplicative model was the best for tree species diversity (AIC=1118.99). The results of analysis of variance showed that the Tanguieta District ($p < 0.006$) and interaction between farm area size and landowners ($p < 0.030$) were positively and significantly affected by farmers' decision for tree selection (Table 4.5). However, area size, landownership, and their interactions with District had no significant effect on farmers' decision for tree selection. For tree species richness, the district ($p < 0.001$) was positively and significantly affected by farmers' decision for tree selection (Table 4. 6). For tree species abundance, area size ($p < 0.001$) and District ($p < 0.001$) were positively and significantly affected by farmers' decision (Table 4.7). This indicated that as farm size increase the tree species abundance correspondingly increase (Figure 4.3). The Figure showed that the Shannon diversity index was more relevant for landowners' farmers than tenant or non-landowner farmers (Figure 4.4). This means that as the farm sizes increase, the tree diversity also increases for landowners. However, the diversity index for tenants decreased for increasing farming size. With respect to the studied districts, the (Figure 4.5) species richness was greater in the Materi District than Tanguieta District implying that the agroforestry units in Materi have diverse tree species.

Table 4.4. Effect of the farm area, landowner and district on the tree species diversity: parameters of the fitted model

	Estimate	Std. Error	t-value	Prob
Intercept	3.59	0.42	8.61	< 0.001
Area	-0.61	0.37	-1.66	0.098
Landowner	-1.18	0.87	-1.35	0.177
District	-1.24	0.45	-2.75	0.006
AreaxLandowner	1.37	0.63	2.18	0.030
AreaxDistrict	0.41	0.41	1.00	0.319
Landowner xDistrict	0.54	0.99	0.55	0.583
AreaxLandownerxDistrict	-0.86	0.69	-1.25	0.212

Table 4.5. Effect of the farm area, landowner and district on the tree species richness: parameters of the fitted model

Variables	Estimate	Std. Error	z-value	Prob.
Intercept	1.37	0.08	16.60	< 0.001
Area	0.02	0.06	0.37	0.715
Landowner	0.13	0.07	1.74	0.082
District	-0.30	0.07	-4.48	< 0.001

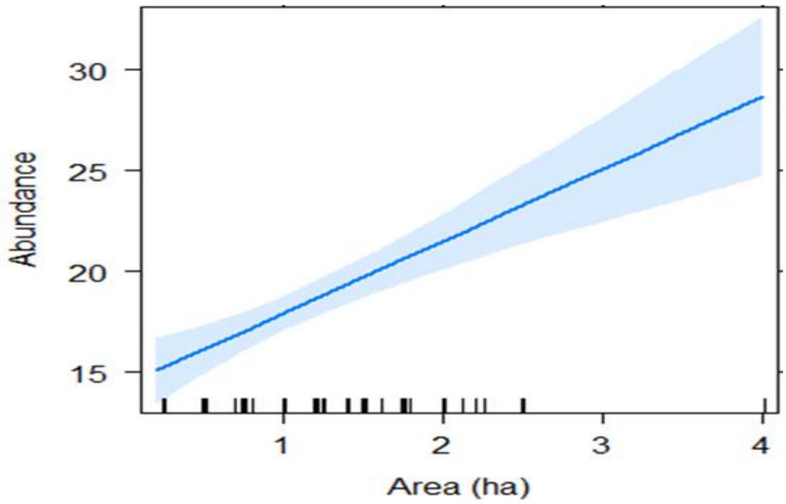

Figure 4.3. Relationship between species abundance and area of agroforestry species

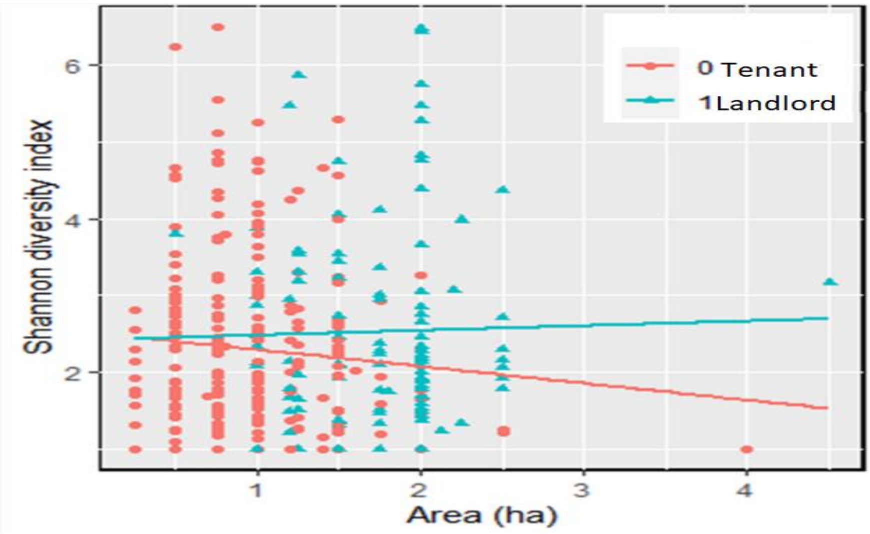

Figure 4.4. Effect of farm area on biodiversity including landholding

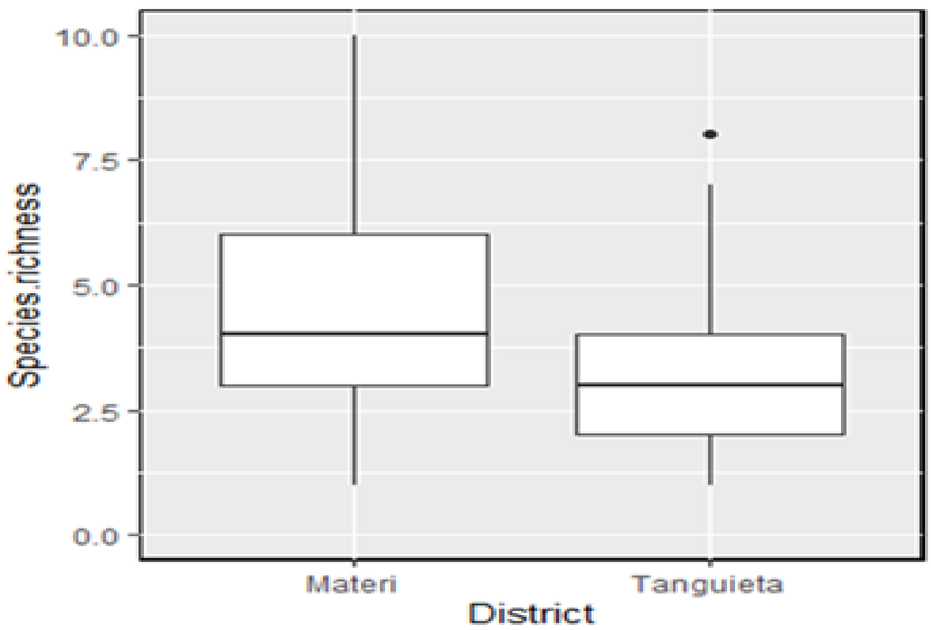

Figure 4.5. Boxplot of species richness according to district

4.3.4. Farmers' preferences for tree and crops association in the agroforestry systems

To assess the preference of farmers for tree and crops associations, the hierarchical cluster analysis (HCA) (Ward, 1963) of farmers was done using their socio-demographic characteristics, ecosystem services, crops and tree abundance. The HCA classified farmers in three different agroforestry system groups as shown by the dendrograms in Figure 4.8. The red color of dendrogram represented the first group (Group1) with 37.50%, the second group (Group 2) is represented by the black color with 50.50% and the third group (Group 3) is represented by the green color of dendrogram with 12% of farmers. Results of the discriminants variables showed that factors such as ethnicity, tree species and crop species were positively and significantly influenced by farmers preferences in all the three groups (Tables 4. 8 and 4.9; Appendix 1 and 2). The combination of HCA with the V-test showed that Group1, represented mainly by Gourmantche ethnic group namely Gourmantche cereal-leguminosae traditional agroforestry had preferred tree species such as: *Afzelia africana, Combretum aculeatum, Diospyros mespiliformis, Balanites aegyptica* (V.test>2, P <0.05) than *Leptadernia hastata, Sarcocephalus latifolus, Dichrostachys cinera,Trichilia emetica, Pseudocedrela kotschyi* and *Daniellia oliveri* associated with *Zea mays* and *Glycine max, Zea mays* and *Vigna unguiculata, Zea mays* and *Vigna subterranea, sorghum bicolor* and *Vignaunguiculata* and monoculture of *Vigna unguiculata* and *Gossypium hirsutum* (V. test ≤ -2, Prob <0.05). However, the second group (Group 2) represented by the Berba ethnic group namely Berba cereal-leguminosea mixed agroforestry systems preferred tree species such as: *Dichrostachys cinera, Daniellia oliveri, Leptadernia hastata, Diospros mespiliformis, Afzelia africana, Pterocarpus erinaceus, P. biglobosa* and *Lannea microcarpa* with *Zea mays* and *Glycine max*; *Sesamum indicum* and *cajanus cajan*, *Zea mays* and *Glycine max, Sesamum indicum* and *Arachis hypogea* (V. test ≥ 2; Prob <0.05). The third group (Group 3) namely Wama's monocropping agroforestry system preferred *Pseudocedrela kotschyi, Trichilia emetica, Sarcocephalus latifolus, Daniellia oliveri, Balanites aegyptica, Combretum aculeatum, Combretum collinum* (V. test ≥ 2; Prob <0.05) in association with *Oryza sativa* and *sorghum bicolor* monoculture (V. test ≥ 2; Prob <0.05). They had less preference for *V. paradoxa* (V. test ≤ -2, Prob <0,05) and this group was represented by Wama ethnic group.

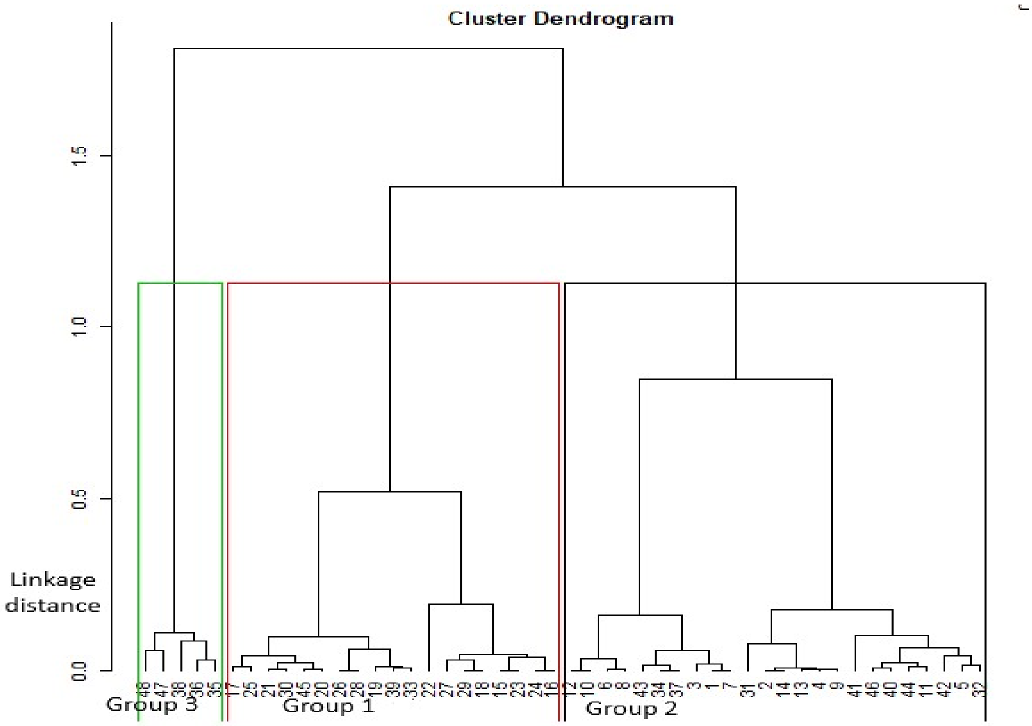

Figure 4.6. Cluster analysis showing different groups of farmers

Table 4.6.Discriminant analysis of tree species enumerated in the Agroforestry systems

Variables discriminants	Chi-2	P-value
Pseudocedrela kotschyi	0.83	0.000
Dichrostachys cinera	0.83	0.000
Daniellia oliveri	0.83	0.000
Trichilia emetica	0.82	0.000
Sarcocephalus latifolus	0.34	0.000
Leptadernia hastata	0.26	0.000
Balanites aegyptica	0.11	0.000
Diospros mespiliformis	0.08	0.000
Afzelia Africana	0.04	0.001
Combretum aculeatum	0.04	0.001
Parkia biglobosa	0.02	0.026

Table 4.7.Discriminant groups and analysis on crops types, ethnic tree benefits

Variable discriminants	Df	Prob
Zea mays Glycine max	4	0.000
Oryza sativa	2	0.000
Supporting services	2	0.000
Zea mays Vigna unguiculata	2	0.000
Sesamum indicum Vigna unguiculata	4	0.000
Regulation services	2	0.000
Ethnic	4	0.035

4.4.**Discussion**

The dominant ethnic groups had social and cultural values that determined their land use practices. Thus, the social and cultural values of the ethnic groups affect their choices of food, staple crops and varieties, and cropping systems. As noted by Clark *et al., (*2022) , different ethnic groups have their own religious beliefs, values and resources that influence their attitude, social norms, and behavioral controls toward agricultural innovation. Similar results have been reported in Indonesia, where the largest ethnic group greatly influenced agricultural practices (Ananta *et al.,* 2016). For instance, in one study, older male people tended to be the majority of landowners with sizable farms. Due to their historically assigned roles in the home, among other things, the women had restricted access to property and showed less interest in tree farming or even joining community organizations. Maskey et al. (2006) reported similar findings that customary circumstances define and affect men's and women's behavior, which provide barriers to participation in resource management initiatives. Men are perceived in social and cultural contexts to be in charge of village development and governance, which reduces women to domestic responsibilities and further restricts them.

The tree species enumerated in the agroforestry systems were mainly of the family Fabaceae, which had 12 different species (Table 4. 2). This might be due to the households' preference being inclined towards the growing of leguminosae and medicinal tree species in their farmlands. Retaining and planting treess in the farming systems were largely determined by space availability and compatibility with agricultural crops and household needs (Lemage & Legesse, 2018). However, farmers in the study area planted or retained different plant species to fulfill the household demand for various products and services such as construction material, food, shade, bee hive, soil fertility and improvement, fuel wood, medicine, income source and fruits. Similar to the findings by (Sood & Mitchell, 2009), the total size of households' landowners had a positive influence on the number tree species grown or retained on farmlands. This was easy to understand because large land will have more space where tree can be grown. As noted by Dhanya *et al., (*2014), households with large land tend to be better off economically and can therefore focus less on optimizing total farm crop output by retaining more tree that can provide environmental benefits. This indicates that as farmers access to land increases, they tend to have greater capacity to adopt different agroforestry systems as adaptation measures to climate change. This situation could be explained by the fact that land is an indispensable asset as far as the practice of different agroforestry systems is concerned. The results however, contrasted with a study from Rwanda, which reported an inverse relation between availability of land and adoption of agroforestry system as climate change adaptation strategy (Ndayambaje, 2013).

Generally, for tree species such as *Anarcadium occidentale*, *Acacia auriculiformis*, *Azadirachta indica*, *Eucalyptus camadulensis, Gmelina arborea* and *Mangifera indica* planted in parks or plantations, the number of tree per hectare (ha) was not important because these tree species are not accessible. However, for natural regeneration parks with important species such as *Vitellaria paradoxa and Parkia biglobosa,* the number of trees per hectare is important. According to respondents by the study participants, landowners of land may set a precondition that land tenants plant tree in the fields rented to them and tenants are required to leave the land when the tree mature. Landowners usually also allow tenants to plant tree for personal uses. But currently, the land is given to tenants only for a limited time leaving the tenants with little right to tree. The effect was that newcomers may never get the same possibilities for income generation from the tree component of tree-crops integration. This was a major concern raised by the smallholder tenant farmers in the study area which might have greatly accounted for the low tree species diversity in agroforestry farmlands of tenant farmers (Figure 4.5).

Farmers can better adapt to climate change by practicing either silvipastoral or agrosilvicultural system of agroforestry. However, only the agrosilvicultural system was observed with mostly fruit tree intercropped with food crops. In the face of climate variability and change, smallholder farmers adopted agrosilvicultural systems as a strategy to enhance their resilience and diversify production. By integrating diverse crop and tree species, farmers aimed to mitigate the impacts of climate change. These findings align with a study conducted by Gnonlonfoun *et al.,* (2019), which highlighted the perception of farmers regarding the resilience of agroforestry systems, specifically parks consisting of *Vitellaria paradoxa*, Anacardium occidentale, and mixed parks of Vitellaria *paradoxa-Parkia biglobosa*, in the context of climate change.

As length of fallow periods have declined, tree and annual crops associations have become a suitable alternatives to shifting cultivation system (Staver *et al.,* 2009). According to Daoui & Fatemi, (2014), tree and crops associations permit increase in yield per unit area, promote species diversity and decrease household's feeding cost. The association also helps to increase the economic efficiency of land and promote rehabilitation of marginal land while improving biodiversity conservation. The farmers reported that the tree and crops integration reduced soil erosion and impacts of strong wind, and increased soil fertility and water efficiency on their farmlands thereby increasing their capacity to adapt to the potential negative impacts of climate change on their livelihoods. Some farmers also revealed that inter crops may benefit from shade which reduced evaporation. Several previous studies have reported similar findings. For instance, Prevedello *et al.,* (2018) found that tree in agricultural landscapes increased yields by reducing risks associated with erosion and temperature fluctuations, while Wolff *et al.,* (2019) reported maintenance of biodiversity and improvement on human health.

The farmers perception that this association of tree and food crops reduces negative impact of rainfall variation depending on the species and their growth cycles. This is consonance with the demonstration that agroforestry has the advantages of diversification of ecosystems, which can preserve and enhance biodiversity, carbon sequestration and efficient use of inputs including land, fertilizer and water. For instance the agroforestry system has been found to reduce soil erosion by up to 65% and nitrogen leaching by about 28% (Palma *et al.,* 2007). According to Nasrullahzadeh *et al., (*2007), it enhanced grain yield of crops by enhancing their reproductive cycle, while the cultivation of crops in association with perennial tree increased farmers' income (Thakur *et al.,* 2018). Tree species that could be more suitable to be associated as inter rows crop should therefore be investigated.

4.5. Conclusions

Climate change is a major factor affecting the agriculture sector and threatening the livelihood of farmers and therefore it is necessary to develop strategies to help farmers adapt to adverse effects of climate change. As shown in this study, farmers' choice of tree and crops integration in agroforestry system as adaption strategy to climate change was influenced by a number of factors. These included land accessibility (landowner, tenants), farm size, location and interaction between landholding and farm size. The most important agroforestry system was agrosilvicultural which promoted the association of local tree species with staple food crops.

Tree benefits were the most important criteria in selection of tree for the agroforestry systems with provisioning followed by supporting services as the most common ecosystem benefit derived by local communities. Tree-crops associations varied among the ethnic groups. Gourmantche preferred *Afzelia africana, Combretum aculeatum, Diospros mespiliformis, Balanites aegyptiaca, Leptadernia hastata, Sarcocephalus latifolus, Dichrostachys cinera, Trichilia emetica, Pseudocedrela kotschyi* and *Daniellia oliveri* associated with *Zea mays* and *Glycine max*, *Zea mays* with *Vigna unguiculata* and *Oryza sativa* in a monoculture. Berba had preference for *Dichrostachys cinera, Daniellia oliveri, Leptadernia hastata, Diospros mespiliformis, Afzelia africana, Pterocarpus erinaceus, Parkia biglobosa* associated with *Zea mays* and *Glycine max*; and *sesamum indicum* with *Vigna unguiculata.* These preferences served to diversify farmers' cropping options to adapt to climate change.

CHAPTER 5: CLIMATE CHANGE AND TREES CONSERVATION IMPACTS ON CROP YIELD IN AGROFORESTRY SYSTEM IN RIVERINE AREA OF PENDJARI RESERVE IN BENIN

Abstract

Agriculture in the Republic of Benin generates around 70% of employment and 30% of GDP, but it is rainfed and vulnerable to climate change. Crop yield gap valuation and clarification can help to identify problems and challenges and to provide solutions with the aim of increasing crop production. This study aimed to (i) assess the impact of climate trends on major crop yield and (ii) evaluate the impact of tree conservation on crop yield in agroforestry systems. Temperature and rainfall data for forty years were obtained from Tanguieta Meteorological station in Benin. The annual crop yield of major crops was obtained from Direction Départementale de l'Agriculture de l'Elevage et de la Pêche of Benin, from 1990 to 2020. Crop yield from the field in 2020 was collected at a distance of 2 m, 4 m and 6 m away from standing trees on the farms. RClimDex was used for the quality control assessment of climate data. Exponential regression model was performed to select parameters that influenced crop yield. There was a general positive warming trend between 1981 and 2020. The findings showed that the minimum temperature and relative humidity positively and considerably impacted maize, but rainfall negatively and strongly (P 0.005Radj^2 =32.3) influenced maize. The minimum temperature and relative humidity had a positive impact on sorghum (P 0.02, R^2 = 9.68). The maximum temperature and relative humidity had negatively and significantly impacted on cotton yield, whereas the rainfall had positively adverse and significant effects (P0.000, Radj^2 = 36.91). Maximum and minimum temperature had positively significantly (P 0.05, R^2 = 54) impacted on cowpea yield. The Exponential regression model's findings indicated that

soil physico-chemical characteristics and tree proximity to crop are the primary variables determining crop yields in agroforestry system.

Keywords: Food security, productivity, climate trends, and Pendjari reserve

5.1.Introduction

Over two decades, climate change has been considered a severe threat to humanity by affecting agricultural productivity (Abbas, 2022). Agriculture is the primary sector in the world that employs 53 % of the rural population, and contributes 25 % of the Gross Domestic Product (GDP) (Imran *et al.,* 2018). A decline in per capita food availability is projected in most African countries (Oluwatayo & Ojo, 2016), and this is aggravated by land degradation (Smethurst *et al.,* 2017). At the same time, average land holdings decrease due to population growth and climate change, and farmers cannot afford to allocate separate areas to grow crops and trees. Yields of main crops in Africa remain lower than those of other continents when compared with potential need that can be obtained with better water and nutrient management (Mueller *et al.,* 2012). More efficient use of resources could reduce this difference between actual and potential yield. Agroforestry is increasingly promoted as the most important tool in addressing African soil fertility issues (Jha *et al.,* 2021). Tree crop integration can often reduce soil erosion, improve water and nutrient cycling, and increase soil organic carbon and the abundance and activity of beneficial soil organisms (Barrios *et al.,* 2012). Despite this sustainability of crops in the long term, the most important challenge is the influence of trees on crop yield due to aboveground competition for light and belowground competition for water and nutrients between crops and trees (van Noordwijk *et al.,* 2021). The net effect of agroforestry on crop yields over time will depend on attributes and interactions of the trees species, canopy cover, diameter, height, crop species, the radial distance of trees on the under crops, soil, climate, and management (Bayala *et al.,* 2012). However, tree crop integration does not always provide a solution, as negative interactions may occur due to competition with adjacent crops (Siriri *et al.,* 2009; Bayala *et al.,* 2012; Craine & Dybzinski, 2013). It is necessary to adopt effective strategies to minimize adverse tree crop interactions. Schreiber *et al.* (2015) suggested two characteristics of trees that can be managed to minimize the adverse competition and limit competition. These characteristics are canopy and root architecture. Root and shoot pruning may be used to control the competitive impact of trees (Siriri *et al.,* 2009). Despite the well documentation of the importance of tree crop integration, less is known about tree's influence on crop yield with regard to tree cover and proximity to crops. This study sought to determine the impacts of climate change and tree conservation on crop yield in the riverine area of Pendjari Reserve in Benin. Specifically, the study aimed to: (i) assess the impacts of temperature and precipitation trends on major crop yields; and (ii) evaluate the impact of tree conservation on major crop yields in an agroforestry system in the Riverine area of Pendjari Reserve in Benin. The study hypothesized that: (i) crop yields do not change with temperature and precipitation trends; and (ii) crop yields in agroforestry system vary according to crop proximity to trees, soil nutrients depending upon the crop species, and tree (species, and canopy cover).

5.3.1. Materials and methods

5.2.1. Climate data

Temperature (maximum and minimum) and rainfall datasets for 1981 – 2020 were obtained from the Tanguieta Meteorological station in Benin in 2022. Gridded datasets were extracted to the coordinates of the meteorological station using nearest neighbor method (NNM) across North Western Benin and covering the period from 1981 to 2020 (Akinsanola *et al.,* 2017). The 1981 – 2020 dataset was used for its consistency, accuracy, and reliability. Non-growing season climatic conditions do not directly influence yields and may contribute to uncertainty in our study (Moreno Cadena & Gourdji, 2015).

5.2.2. Crop yield data

The four major crops assessed in this study are *Sorghum bicolor, Zea mays, Gossypium and Vigna unguiculate.* Records of the annual crop yields were acquired from the Direction Départementale de l'Agriculture de l'Elevage et de la Pêche (DDAEP/Atacora), a subdivision under the Ministry of Agriculture, Livestock and Fisheries of the Republic of Benin for the same period of the climate dataset (1981 – 2020).

5.2.3. Sampling Design and Methods of field data Collection

Farmers who cultivate *Zea maize*, *Sorghum bicolor, Gossypium bicolor* and *Vigna unguiculata* and were not applying inorganic fertilizers were randomly selected per site for the study. Within each crop field, all measurements were performed along a transect of 100 m long on the longest diagonal of the field starting from the northwestern vertex. The choice of field edge was mostly driven by convenience with agroforestry practices (associated trees and crops) and the absence of widening practices. However, peculiar locations, such as adjacency with woodland, were avoided. Three equidistant sampling plots of 30 m×30 m were set along the diagonal line. Tree geometric characteristics, crop yield per plot, and distance from tree trunk and crop at 2 m, 4 m and 6 m were measured. *Parkia biglobosa, Vitellaria paradoxa* and *Lannea microcarpa* were considered, and under each tree species one meter by one-meter square quadrat (1 m×1 m) from inside to outside was made at a distance of 2 m, 4 m and 6 m away from tree trunk in four compass directions (North, South, East and West) (see Figure 5.1). Quadrat from the same radial distance in the four campass directions were regarded as replicates. All the grain plants within each quadra were harvested, and the grains separated from the stalk. The grains within each quadrat were weighed with a sensitive weighing balance.

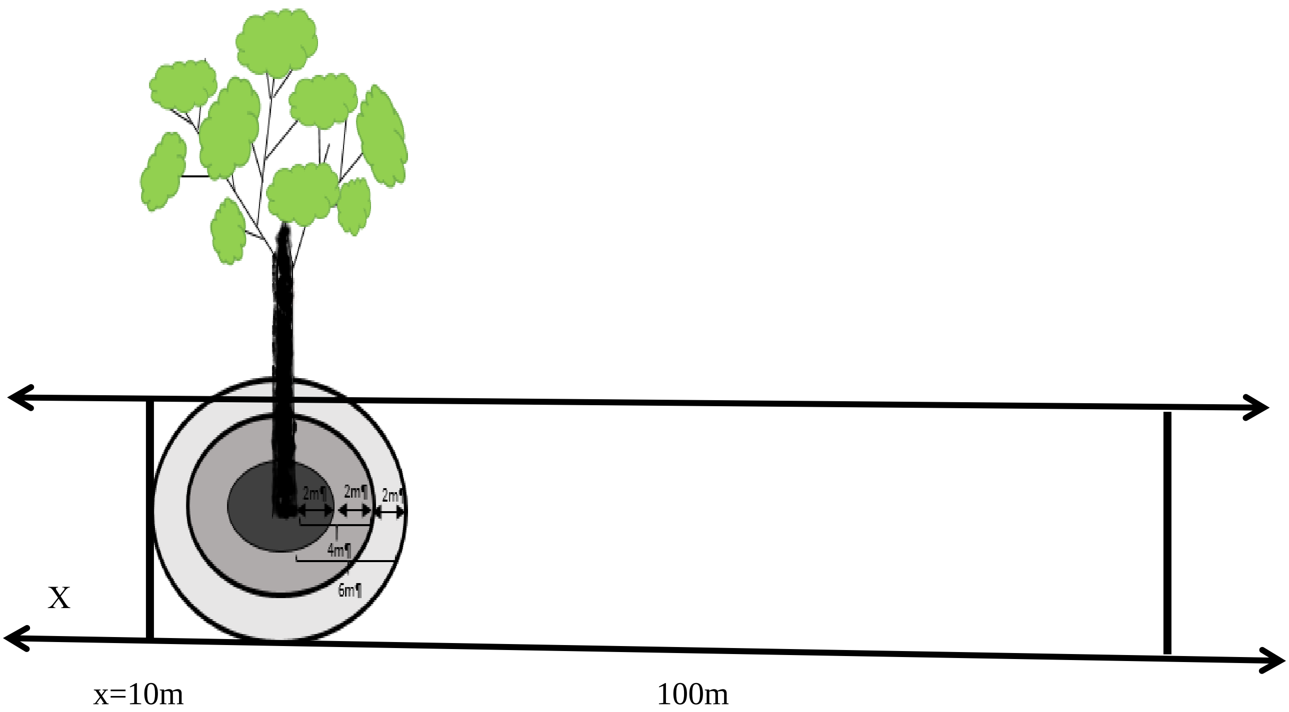

Figure 5.1. Plot sampling are distributed on the field

From each 30 m×30 m plot, soil samples were collected at 2 m, 4 m and 6 m away from the tree trunk four different depths (0-10 cm, 10-20 cm, 20-30 cm, and 30-40 cm) using a core sampler measuring 9 cm in height and 5.5 cm in width. Each sample was placed in labeled zip-lock bags. This sampling procedure was conducted twice in each quadrat to determine bulk density and perform nutritional analyses. While the samples for bulk density were collected individually, the fertility studies from the three quadrats were combined (pooled) into a single composite sample for each depth per plot.

5.2.4. Data Analysis

5.2.4.1. Climate Analysis

To ensure data quality, a quality control check was conducted using RClimDex, and stations with more than 5% of missing data and outliers were eliminated from the dataset. Furthermore, a homogeneity test was performed using the RHtest package in R software (R Core Team, 2019) to assess fluctuations in the data. Various climate parameters, including rainfall, minimum temperature (Tmin), maximum temperature (Tmax), mean temperature (Tmean), Standardized Precipitation Index (SPI), and Standardized Precipitation Evapotranspiration Index (SPEI), were analyzed to determine their trends. Additionally, the correlation between crop yield and these parameters was established using RClimDex. These parameters were considered as influential factors on crop yields, as they are included in ClimPACT2, which incorporates the Standardized Precipitation Index (SPI) proposed by McKee et al. (1993) and accepted by the World Meteorological Organization (WMO) as the standard drought index for effective drought monitoring and climate risk management (WMO, 2012). Additionally, the Standardized Precipitation Evapotranspiration Index (SPEI) proposed by Vicente-Serrano et al. (2010) was used, which combines sensitivity to changes in evaporative demand caused by temperature fluctuations and trends, with the simplicity of calculation and the multi-temporal nature of SPI. The RClimDex tool was utilized to explore the correlation between crop yield and climate, providing insights into the positive or negative associations that aid in understanding the regression results.

5.2.4.2. *Effect of Climate on crop yield*

Correlation coefficient (r) was used to estimate the impact of climate variables on the yields of the selected staple food crops over a 30-year period (1990-2020), indicating the sensitivity of the crop yields to climate variability. This method has been used extensively in analyzing the effect of climate variability on food production (Rowhani *et al.,* 2011).

5.2.4.3. *Effect of tree conservation characteristics on crop yield*

Soil sampling was analyzed in the Laboratory (Laboratoire Sciences du sols) at the University of Abomey-Calavi The soil samples underwent the following processes: air-drying, passing through a 2-mm screen, and subsequent laboratory analysis to assess various characteristics. Soil organic carbon (SOC) was measured using the modified Walkley-Black dichromate oxidation technique (Nelson and Sommers, 1982). Total nitrogen (TN) was calculated using the Kjeldahl digestion and distillation method (Mulvaney, 1982). The easily acid-soluble forms of phosphorus (P) were extracted using an HCl: NH4 Mixture (Bray's No. 1 extract), and their calorimetric values were obtained through ascorbic reduction (Bray and Kurtz, 1945; Sommers, 1982). Sieving was employed to remove roots and stones larger than 2 mm from the soil samples used to determine bulk density. Subsequently, the samples were dried in an oven at 105°C for 48 hours. The oven-dried soil samples were used to estimate soil bulk density based on their dried weight and volume. Soil C stock was estimated according to (Adu Bredu *et al.,* 2021) using Equation (5.3)

$$SCS = SOC*BD*DP \quad [5.3]$$

Where SCS is soil carbon stocks (Mg C ha-1), SOC is soil organic carbon content (%), BD is bulk density of soil (g cm-3) and Dp is soil depth (m). The total SCS up to 40 cm depth was finally estimated by summing up the C content of all layers (Pearson, 2005). An Exponential regression model was used to investigate the relationship between the yield of plants and several predictor variables, including tree species, distance, phosphorus, bulk density, nitrogen, carbon.

Modeling Exponential Regression

A list of unique species-crop combinations was generated. For each species-crop com bination, the data were filtered to include only observations for that specific combinat ion. The nlsLM function was used to fit an exponential model of the form Yield ~ A * exp (B * Distance) to the filtered data. The model parameters A and B were initialize d as A = 1000 and B = -0.1. The fitted models were stored in separate lists (exponenti al_models1 and exponential_models2). The summary of each fitted model was printe d to examine the fitted parameters, standard errors, and significance.

Empty vectors (rsquared_values and adjusted_rsquared_values) were initialized to sto re R-squared and adjusted R-squared values. For each species-crop combination, the R- squared value was calculated using the formula 1 - (rss / tss), where rss is the resid ual sum of squares and tss is the total sum of squares. The adjusted R-squared value w as calculated using the formula 1 - ((1 - R-squared) * (n - 1)) / (n - k - 1), where n is t he number of data points and k is the number of independent variables. The calculate d R-squared and adjusted R-squared values were stored in the respective vectors."

5.3.Resultsclimate variability and crop yield

5.3.1.1. Trend analysis of climatic variables

Table 5.1 reveals a notable increase in average Tmin and Tmax across the study area from 1981 to 2020, indicating a significant positive warming trend. The monthly hottest daily trend has increased, indicating a positive value of Sen's slope (0.002) with a significant value (0.013). This positive trend in the hottest daily signifies that the study area is experiencing increased incidents in the maximum temperature extremes. The monthly mean daily minimum temperature showed a significant positive trend. However, the mean annual difference between daily Tmax and Tmin showed a significant negative trend. There was significant increasing (positive) trend of annual rainfall (annual sum of daily precipitation ≥1.mm), evidenced by the positive Sen's slope of 4.28 (Table 5.1). Growing degree days change indicated a positive value of Sen's slope (3.49) with a significant value (0.003). Table 5.1 presents the Standardized Precipitation Index (SPI3, 6, and 12), which indicates a significant positive trend. The validity of this trend is further confirmed by the Standardized Precipitation Evapotranspiration Index (SPEI 3, 6, and 12), which exhibits significant positive values for Sen's slope (0.002, 0.03, and 0.04) respectively. In the Sudanian zone of Benin, where evaporation rates are high, the SPEI provides a more comprehensive assessment of drought evolution by considering both temperatures and rainfall, thus capturing the influence of global warming.

Table 5.1.Rainfall and temperature patterns from 1981 to 2020

Number	Index	Frequences	Start year	End year	Slope	P value
1	SPEI3: Standardised Precipitation Evapotranspiration Index of 3 month	Monthly	1981	2020	0.002	0
2	SPI3: Standardised Precipitation Index of 3month	Monthly	1981	2020	0.001	0
3	SPEI6: Standardised Precipitation Evapotranspiration Index of 6 month	Annually	1981	2020	0.003	0
4	SPI6: Standardised Precipitation Index of 6 month	Annually	1981	2020	0.002	0
5	SPEI12: Standardised Precipitation Evapotranspiration Index of 12 month	Annually	1981	2020	0.004	0
6	SPI12: Standardised Precipitation Index of 12 month	Annually	1981	2020	0.003	0
7	CSDI: Cold spell duration indicator	Annually	1981	2020	-0.188	0.019
8	dtr: Mean annual difference between daily maximum temperature (TX) and minimum temperature (TN)	Annually	1981	2020	-0.023	0.037
9	gddgrow20: Growing Degree Days	Annually	1981	2020	3.49	0.003
10	hddheat28: Heating Degree Days Annual sum of 28 TM	Annually	1981	2020	-1.893	0.019
11	prcptot: Annual sum of daily precipitation≥1.mm	Annually	1981	2020	4.28	0.005
12	r 10mm: Annual number of days when precipitation ≥10mm	Annually	1981	2020	0.279	0.014
13	tmm: Annual mean daly mean temperature 0.01	Annually	1981	2020		0.005
14	tnm: Annual mean daly minimum temperature	Annually	1981	2020	0.022	0
15	tnm: Monthly mean daily minimum temperature (TN)	Monthly	1981	2020	0.002	0.009
16	tnx: Monthly warmest daily minimum temperature (TN)	Monthly	1981	2020	0.002	0.013

5.3.1.2. .Impact of historical climate trends on yields

In order to assess the extent to which changes in climate trends explain variations in yield, a linear regression model was utilized. The model estimated the R^2 adj value, representing the correlation between detrended yields and climate variables. The analysis of the results, as presented in Table 5.2, indicate a significant association between changes in temperature and relative humidity and the yield of Zea mays (R^2 *adj* = 32.3; *P* =0.005). Specifically, minimum temperature, rainfall, and relative humidity were identified as influential factors in explaining the yield changes. However, this study revealed that changes in maximum, rainfall and relative humidity significantly affected Gossypium hirsutum yield (R^2 = 36.91, *P* <0.05). Moreover, changes in maximum and minimum temperature had a significant influence on *Vigna unguiculata* yield (R^2 = 49.35 *P* = 0.000). Additionally, the analysis of the results in Table 5.2 revealed that changes in temperature accounted for (R^2 =9.68) of the variation in *Sorghum bicolor* yield (P=0.02), with minimum temperature and relative humidity identified as the driving factor.

Table 5.2.Influence of climate parameters on crop yields.

Cowpea (*Vigna unguiculata)*					
Models	Estimate	Std Error	P value	R^2	R^2 Adj
Intercept	-4745.36	1128.11	0.000***	53.57	49.35
Maximum temperature	114.07	25.44			
Minimum temperature	25.68	5.74			
Cotton *(Gossypium hirsutum)*					
Models	Estimate	Std Error	P value	R^2	R^2 Adj
Intercept	9402.87	2091.81	0.000 ***	44.80	36.91
Maximum temperature	-158.63	46.10			
Rainfall	37.08	23.73			
Relative humidity	-45.93	12.39			
Maize *(Zea mays)*					
Models	Estimate	Std Error	P value	R^2	R^2 Adj
Intercept	-12467.33	4009.47	0.005 **	40.76	32.3
Minimum temperature	459.11	154.73			
Rainfall	-59.51	32.24			
Relative humidity	53.83	15.79			
Sorghum(Sorghum bicolor)					
Models	Estimate	Std Error	P value	R^2	R^2 Adj
Intercept	-1663.72	1267.60	0.2	17.21	9.68
Minimum temperature	92.10	50.41			
Relative humidity	7.23	4.11			

5.3.1.3. Correlation of climate parameters on crop yields

The impact of rainfall and temperature on *Zea mays* yield was illustrated in Figure 5.2. The analysis revealed that temperature predictors exerted a greater influence on *Zea mays* yield compared to rainfall predictors. Specifically, Tropical nights and coldest daily temperatures positively influenced *Zea mays* yield, while Hottest day, Cold spell duration indicator, Maximum amount of rain that falls in three consecutive days, and coldest daily temperatures showed a negative influence (Figure 5.2). In terms of rainfall predictors, consecutive wet days exhibited a positive influence on Zea mays yield with an r-value of 0.56. However, the Maximum amount of rain that falls in five consecutive days and daily precipitation had a negative influence on Zea mays yield, respectively. (Figure 5.2).

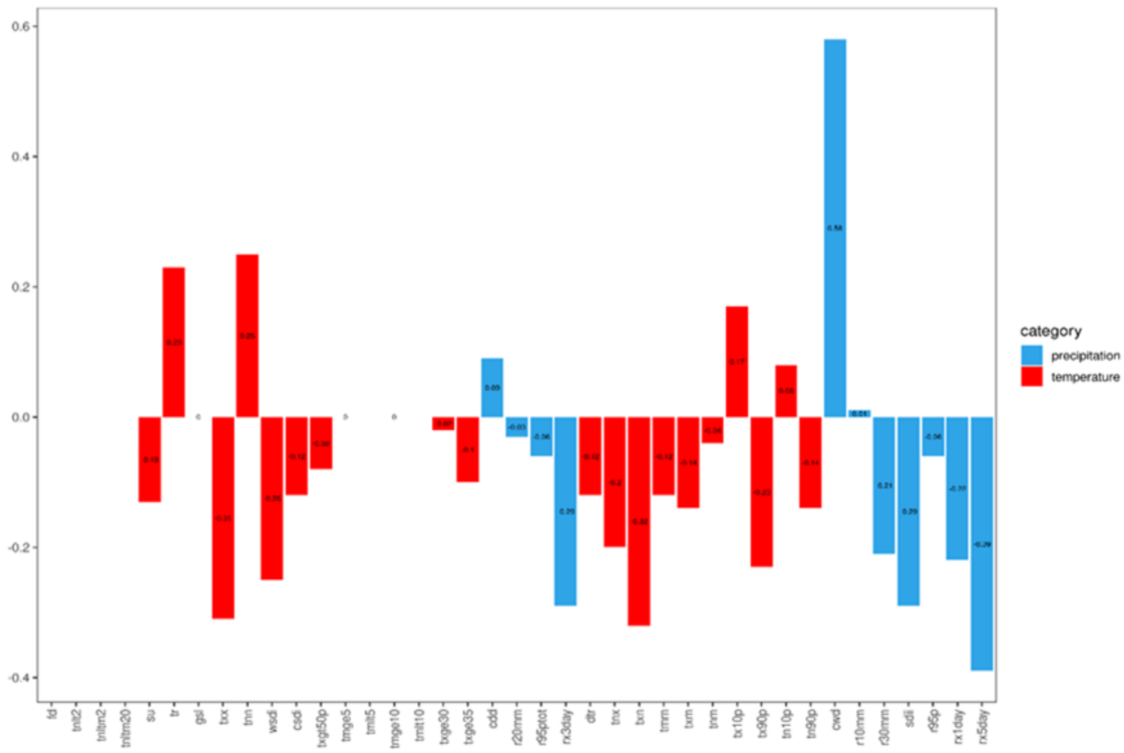

Figure 5.2.Influence of rainfall and temperature on *Zea mays* yield.

The findings demonstrate that temperature predictors have a stronger positive impact on *Sorghum bicolor* yield compared to rainfall predictors. For instance, the growing season length, days with an average temperature of at least 10°C, and the number of cold nights positively influence *Sorghum bicolor yield*. Conversely, tropical nights, warmest daily temperature, mean daily mean temperature, mean daily minimum temperature, and coldest daily temperature negatively affect *Sorghum bicolor* yield (Figure 5.3). As for the rainfall predictors, consecutive dry days, the maximum amount of rain that falls in three consecutive days, the number of heavy rain days, daily precipitation intensity, and the maximum amount of rain that falls in five consecutive days showed a very low positive influence on *Sorghum bicolor* yield. However, the number of very heavy rain days, contribution from very wet days, consecutive wet days, and total annual precipitation from heavy rain days negatively impacted *Sorghum bicolor* yield (Figure 5.3).

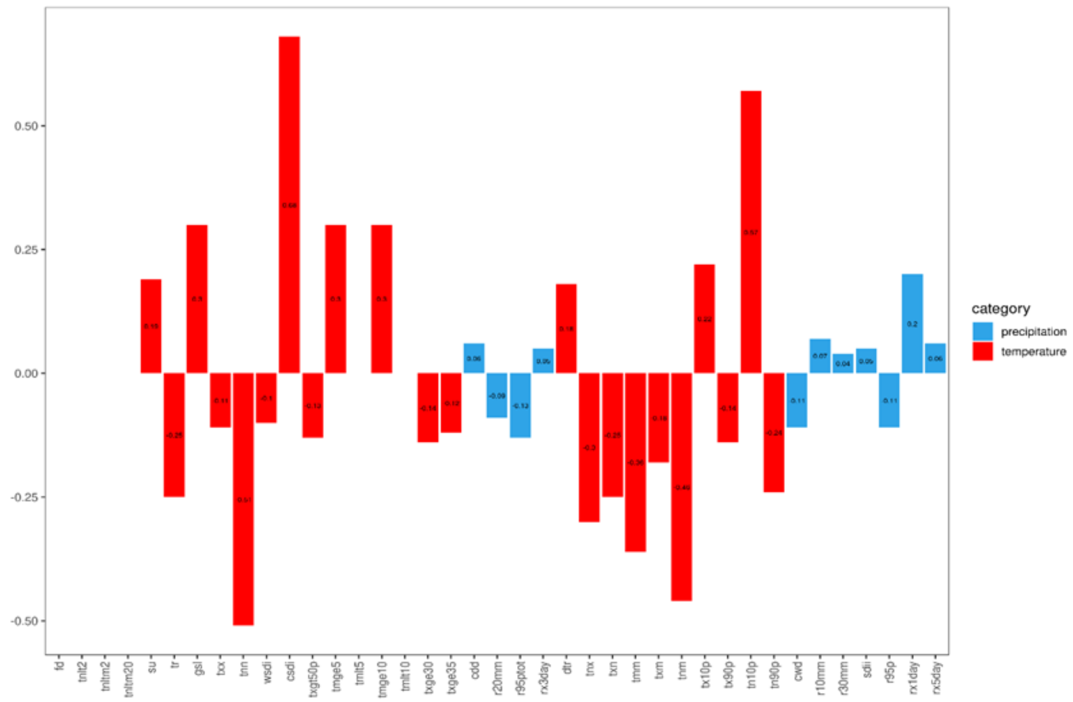

Figure 5.3.: Influence of temperature and rainfall on *Sorghum bicolor* yield

The impact of rainfall and temperature on *Gossypium hirsutum* yield was illustrated in Figure 5.4. The results indicate that temperature predictors exert a stronger influence on *Gossypium hirsutum* yield compared to rainfall predictors. For instance, summer days, tropical nights, growing season length, and the number of days with maximum temperature (TX >=30°C) positively influence *Gossypium hirsutum* yield. However, the warmest daily temperature and cold spell duration indicator have a negative impact on *Gossypium hirsutum* yield. Regarding the rainfall predictors, consecutive dry days, the maximum amount of rain that falls in three consecutive days, and the number of heavy rain days positively influence *Gossypium hirsutum* yield. Conversely, consecutive wet days have a negative impact on *Gossypium hirsutum* yield (Figure5.4).

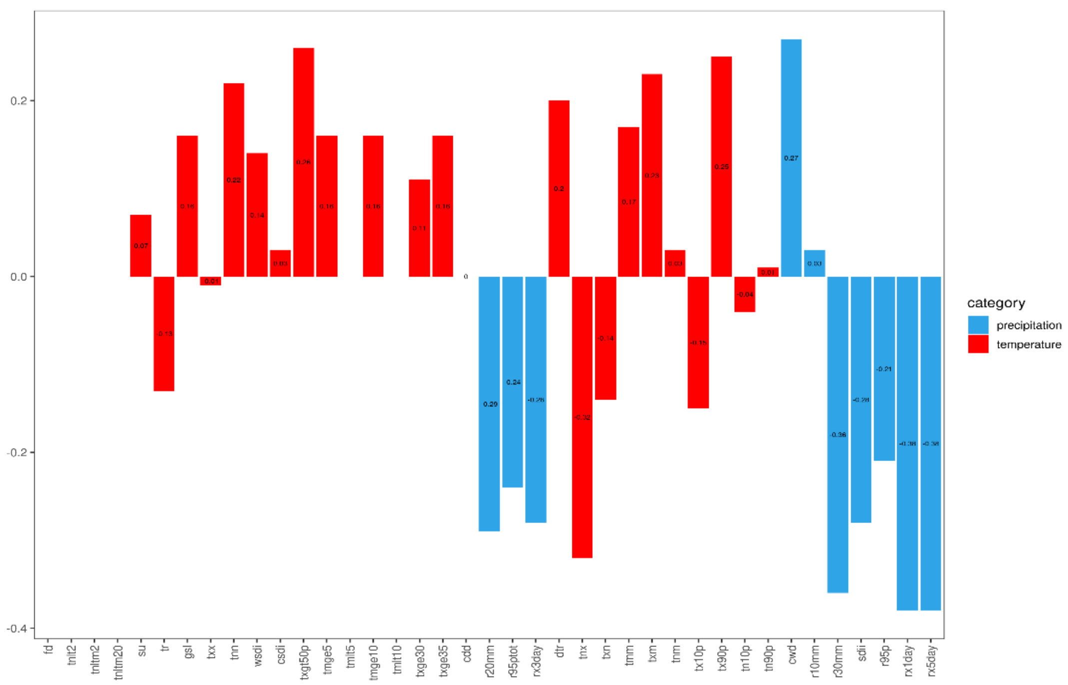

Figure 5.4. Influence of temperature and rainfall on Vigna unguiculata yield.

The influence of rainfall and temperature on *Vigna unguiculata* yield was presented in Figure 5.5 The results indicate that temperature predictors have a stronger impact on *Vigna unguiculata* yield compared to rainfall predictors. For instance, the number of hot days, mean daily maximum temperature, coldest daily temperature, and the percentage of days where the temperature reaches the maximal (TX >50th) percentile positively influence *Vigna unguiculata* yield. Conversely, the warmest daily temperature, amount of cool days, coldest daily temperature, and tropical nights negatively affect *Vigna unguiculata* yield (Figure 5.5). In terms of rainfall predictors, consecutive wet days positively influence *Vigna unguiculata* yield. However, the maximum amount of rain that falls in five consecutive days, total annual precipitation from heavy rain days, daily precipitation intensity, the number of days with precipitation (P >= 30mm), the number of days with precipitation (P >= 20 mm), contribution from very wet days, and the maximum amount of rain that falls in three consecutive days negatively influence *Vigna unguiculata* yield (Figure 5.5).

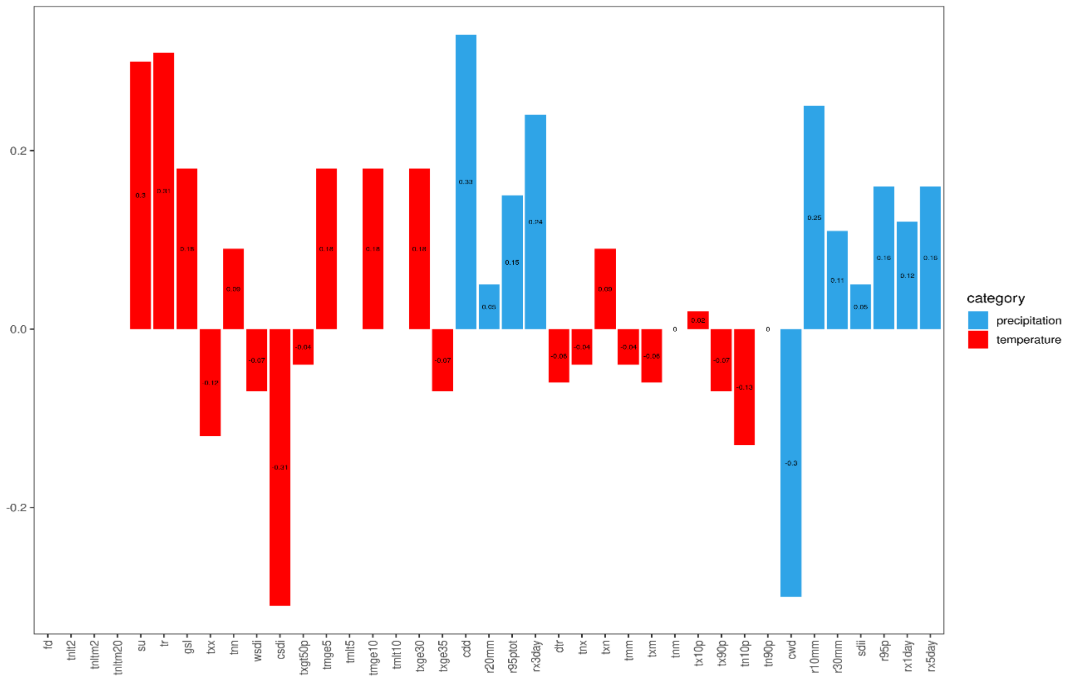

Figure 5.5.Influence of temperature and rainfall on Gossypium hirsutum yield

5.3.2. Factors influence crop yields in the agroforestry system

The analysis of Exponential Regression demonstrated that the grain yield of *Zea mays* exhibited significant variations depending on the tree species and distance (Figure 5.6). Specifically, the highest yield of *Zea mays* was observed at 2 m under *Vitellaria paradoxa and 6 m* under *Lannea microcarpa.* Conversely, the lowest yield was recorded under *Parkia biglobosa.* Similarly, the yield of *Vigna unguiculata* showed distinct patterns, with an increase from inside to outside under *Parkia biglobosa.* The highest yield of *Vigna unguiculata* was found at 6 m under the same tree. *Sorghum bicolor* displayed contrasting results, with the highest yield at 6 m and the lowest yield at 2 m under *Vitellaria paradoxa.* Lastly, *Gossypium hirsutum* exhibited an increasing trend from inside to outside, with the highest yield recorded at 6 m under *Vitellaria paradoxa* and the lowest yield under *Parkia biglobosa*

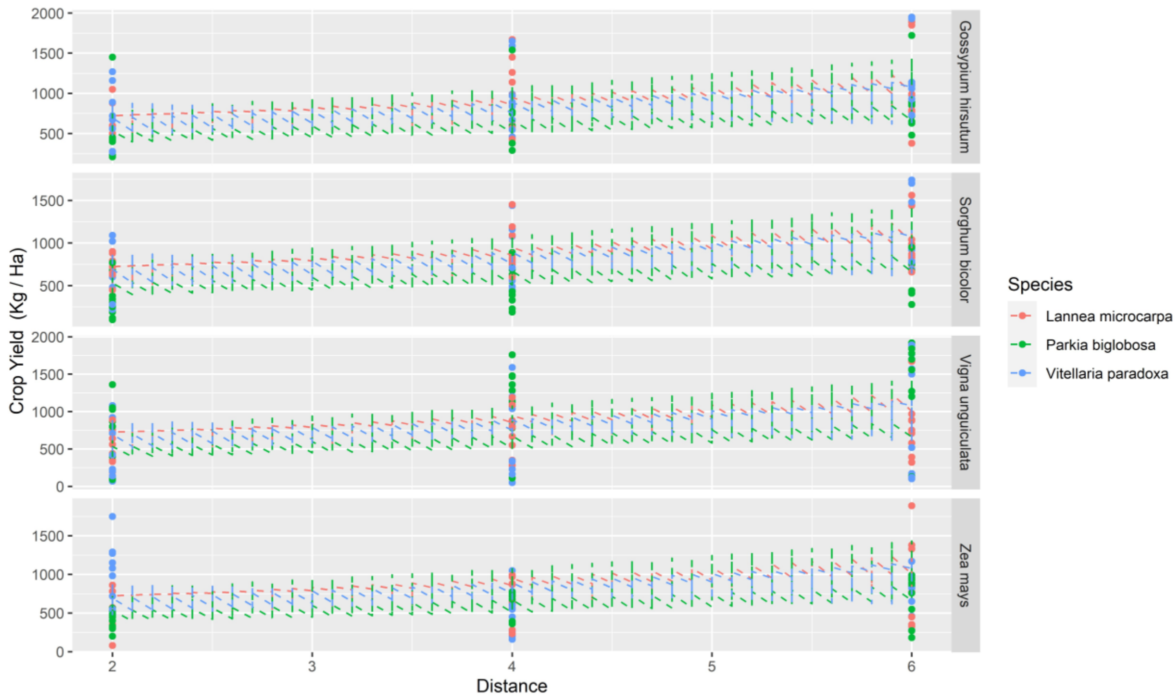

Figure 5.6: Crop yield variation in agroforestry system

From the results, different models were elaborated to predict crops yield under trees species according to distance, carbon, nitrogen and bulk density.

Table 5.3.Crop yield prediction in agroforestry system

Combination of variable	Models	R^2	R2 Adj
Vitellaria paradoxa – Sorghum bicolor	Yield = 0.96781*exp(0.18379) * Distance * Carbon * N * P * BD	92.0	91.4
Parkia biglobosa – Sorghum bicolor	Yield = 1.08628*exp(0.15002) * Distance * Carbon * N * P * BD	80.7	79.3
Lannea microcarpa – Sorghum bicolor	Yield = 1.01463* exp(0.11896) * Distance * Carbon * N * P * BD	75.6	73.7
Lannea microcarpa –Vigna unguiculata	Yield = 0.99166* exp(0.13118) * Distance) * Carbon * N * P * BD	99.1	99.1
Parkia biglobosa – Vigna unguiculata	Yield = 2.78653*exp(0.15339)* Distance * Carbon * N * P * BD	88.8	87.9
Vitellaria paradoxa –Vigna unguiculata	Yield = 0.6555*exp(0.1910)* Distance * Carbon * N * P * BD	95.8	95.5
Lannea microcarpa – Zea mays	Yield = 0.96648*exp(0.14466)* Distance * Carbon * N * P * BD	99.1	99.0
Vitellaria paradoxa – Zea mays	Yield = 5.6627*exp(-0.1445)* Distance * Carbon * N * P * BD	33.7	28.8
Parkia biglobosa – Zea mays	yield = 0.7144exp (0.1321)* Distance * Carbon * N * P * BD	92.0	91.4
Lannea microcarpa – Gossypium hirsutum	Yield = 1.39536exp (0.13619)* Distance * Carbon * N * P * BD	88.3	87.4
Parkia biglobosa – Gossypium hirsutum	Yield = 2.32953exp(0.10313)* Distance) * Carbon * N * P *BD	96.4	96.2
Vitellaria paradoxa – Gossypium hirsutum	Yield = 1.37923exp(0.08657)* Distance * Carbon * N * P * BD	99.9	99.9

5.4.Discussion

The analysis of temperature trends in the study area from 1981 to 2020 reveals a significant positive warming trend, with notable increases in average Tmin and Tmax. This finding aligns with the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2013), which reported a global warming trend of 0.85 (0.65–1.06) °C from 1880 to 2012. However, there is a significant negative trend in the mean annual difference between daily Tmax and Tmin. Sen's negative value indicates that the increase in minimum temperature is greater than the increase in maximum temperature, which is consistent with global observations from 1981 to 2020 (IPCC, 2013). These results are also in agreement with a study by Ajetomobi *et al.,* (2011) in Nigeria from 1971 to 2000. In addition to temperature trends, other studies have shown a general tendency of decreased annual total rainfall and maximum number of consecutive wet days. However, certain indices indicate an increase in the frequency of extreme rainfall events during the last decade (Mouhamed *et al.,* 2013). These findings suggest that while overall rainfall has decreased, there is an intensification of extreme rainfall events.

During the cropping season, the Standardized Precipitation Evapotranspiration Index (SPEI) at 3, 6, and 12-month lags demonstrates an increasing trend, reflecting alternating periods of dryness and rainfall. This trend characterizes the severity, extent, and duration of drought (Jabbi *et al.,* 2021). The results of the study indicate an upward trend in SPEI across the study area. These findings align with recent studies conducted in Africa and other regions, which emphasize the occurrence of fluctuating wet and drought episodes and the increasing frequency of extreme events based on long-term observed data (Jabbi *et al.,* 2021).

The study identifies minimum temperature, rainfall, and relative humidity as influential factors in explaining changes in crop yield. Previous research by Baudron *et al.,* (2019) reported a 45% reduction in maize yield in Ghana in 2017 due to an attack by fall armyworm. However, the study reveals that changes in maximum temperature, rainfall, and relative humidity significantly affect Gossypium hirsutum yield ($R2 = 36.91$, $P < 0.05$). This finding is consistent with Dossou-Aminon et al. (2016), who identified four levels of climate change impacts on crop production: reduced productivity (30.7%), loss or abandonment of landraces (22%), increased damage by storage insect pests (19.3%), early drying of crops (18.7%), and seed rot in the soil due to excessive heat (9.3%).

Changes in maximum and minimum temperature have a significant influence on Vigna unguiculata yield ($R2 = 49.35$, $P = 0.000$). These results align with previous studies conducted in cowpea (Ajetomobi *et al.,* 2011) as well as studies in Kenya (Bryan *et al.,* 2013), Ghana (Etwire et al., 2013), Mali (Traore et al., 2014), and Burkina Faso (Sultan *et al.,* 2013). Furthermore, the results in Table 5.2 indicate that changes in temperature account for $R2 = 9.68$ of the variation in Sorghum bicolor yield ($P = 0.02$), with minimum temperature and relative humidity identified as the driving factors.

Prasad and Snyder (2006) reported similar findings, providing further evidence of the detrimental effect of high temperatures on sorghum productivity. In the case of Zea mays, Tropical nights and coldest daily temperatures have a positive influence on yield, while factors such as Hottest day, Cold spell duration indicator, Maximum amount of rain that falls in three consecutive days, and coldest daily temperatures negatively impact yield. These findings are consistent with the results reported by Yirga *et al.,* (2022) across different regions of Ethiopia.

The study demonstrates that temperature predictors have a stronger positive impact on Sorghum bicolor yield compared to rainfall predictors. For example, factors such as growing season length, days with an average temperature of at least 10°C, and the number of cold nights positively influence Sorghum bicolor yield. On the other hand, temperature predictors have a stronger influence on Gossypium hirsutum yield compared to rainfall predictors. Among the rainfall predictors, consecutive dry days, the maximum amount of rain that falls in three consecutive days, and the number of heavy rain days positively influence Gossypium hirsutum yield, while consecutive wet days have a negative impact.

Furthermore, the results indicate that certain temperature factors, including the number of hot days, mean daily maximum temperature, coldest daily temperature, and the percentage of days where the temperature reaches the maximal (TX >50th) percentile, positively influence Vigna unguiculata yield. Conversely, factors such as the warmest daily temperature, number of cool days, coldest daily temperature, and tropical nights negatively affect Vigna unguiculata yield. It is important to note that increases in extreme temperatures can lead to significant yield reductions and have a negative impact on the reproductive stage of many crops (Hatfield & Prueger, 2015).

The analysis of Exponential Regression revealed that the grain yield of Zea mays was highest at a distance of 2 m under Vitellaria paradoxa and 6 m under Lannea microcarpa. Conversely, the lowest values were observed under Parkia biglobosa, which exhibited the largest canopy cover. This larger canopy negatively impacted soil nutrients, light availability, and water infiltration. This result aligns with the findings of Chauhan *et al., (*2012), who reported a decrease in the growth and yield of Triticum aestivum with increasing poplar canopy size. The results indicated that the yield of Vigna unguiculata increased from the inside to the outside under Parkia biglobosa, with the highest yield recorded at a distance of 6 m from the tree. *Sorghum bicolor* demonstrated the highest yield at 6 m, while the lowest yield was recorded at 2 m. Similar trends were observed by Bayala *et al., (*2012), who reported a decrease in sorghum bicolor yield from the open area to the trunk of néré trees due to shade effects. Regarding *Gossypium hirsutum*, the results indicated an increasing trend in yield from the inside to the outside. The highest yield was recorded at 6 m under Vitellaria paradoxa, while the lowest yield was observed under Parkia biglobosa. This trend of increasing grain yield with distance from the tree trunks was consistent with the findings of Ogwok *et al.,* (2019), who highlighted the responsiveness of *Gossypium hirsutum* to light intensity and temperature. Microfaunal activities, water availability and the incidence of solar radiation were the three main factors that explained the observed variation of soil nutrients abundance under the tree species canopy in agroforestry system (Gnanglè *et al.,* 2013).

5.5.Conclusions

Climate variability's impact on crop yield mainly depends on the crop species. The findings showed that cool-season species would be more affected because of an increase in average temperature**.** The Hottest and monthly mean daily minimum temperature trends significantly influence crop yield. However, the mean annual difference between daily maximum and minimum temperature negatively and significantly affects crop yield. Results showed an increasing pattern of yearly rainfall and growing degree days. Maximum and minimum temperatures influenced cereal crops like Zea mays and Sorghum bicolor. Climate variability remains as crucial as soil management, diseases and pest control, seed quality, and technology in influencing crop yield variation.

The results of the Exponential regression model indicate that tree species proximity and soil nutrients influencing the yield of maize, cotton, cowpea, and sorghum in agroforestry systems.

CHAPTER 6:CARBON SEQUESTRATION IN AGROFORESTRY SYSTEM

Abstract

Carbon storage and sequestration are among the most crucial services provided by forest ecosystems, making them highly effective tools for mitigating and adapting to climate change. People often take these ecological services for granted and do not fully recognize or cherish them. This study looks at the carbon stored and valuation and assesses carbon credit around the riverine area of Pendjari Reserve. Specifically, this study wants to (i) assesses LULC from 1998 to 2020, (ii) evaluate land use change impact on carbon storage, and (iii) predict the future trend of carbon sequestration and valuation for 2035 and 2050. The results show that the maximum carbon is stored by wooded savannah (494,198.1 Mg C ha-^{1}) in 2050, and decreased in 2020 and 2035 respectively (387,059.4 Mg C ha-^{1}) and (387,047.2 Mg C ha^{-1}). The greatest carbon projected to be sequestered from the period 2020-2050 and 2035-2050 with their values being 50,950.97 Mg ha^{-1} and 50,893.4 Mg ha^{-1} respectively. The lowest projected value of 798.12 Mg ha-^{1} was for the period 2020-2035 over fifteen years. The projected highest gain and loss of sequestered carbon was found for the period 2020-2050 and 2035-2550 with the values of 108947 Mg and -57996 Mg ha^{-1} and 108878 Mg ha^{-1} and -57984.6 Mg ha^{-1}, respectively. However, the lowest gain and loss were observed from period 2020-2035 with the values 845.56 Mg ha^{-1} and -47.52 Mg ha^{-1}, respectively. However, projected economic gain indicates a positive value in net present value (NPV) of €171,067 to €90,431, and €90,431 to €285,121 for the same period. The total economic value of carbon sequestration within riverine area of Pendjari reserve was estimated at US$ 3,352,104 for 15 years (2020-2035), US$ 213,994.1 for 30 years (2020 – 2050), and US$ 213,752.3 for 15 years (2035-2050). For the same period, the economic value of carbon sequestration loss was estimated at

US$ 199,584, US$ 243,583.20 and US$ 243,535.3 for the period 2020-2035, 2020-2050 and 2035-2050, respectively.

Keywords: Economic value, aboveground, belowground, carbon sequestration, and wood density.

6.1. Introduction

The world's ecosystem services are declining, affecting forest-dependent communities (Kyere-Boateng & Marek, 2021). The pressure result from changes in land use practices, infrastructure development, unsustainable tourism, fragmentation of habitats, and climate change (Prokopová *et al.,* 2019). Climate and land use change are recognized as international environmental issues (Mendoza-Ponce *et al.,* 2021). However, the origin and sinks of carbon from land use land cover change are fundamentals in the global carbon budget (Chabi *et al.,* 2016a). Carbon storage is the cumulative amount of carbon stored in a terrestrial ecosystem (He *et al.,* 2016). Carbon storage includes four components, according to Liu *et al.,* (2022), which are aboveground carbon storage (AGC), belowground carbon storage (BGC), soil organic carbon storage (SOC), and dead organic matter carbon storage (DOC). Carbon storage is a crucial indicator of ecosystem services as it is closely linked to the productivity and climate regulation of terrestrial ecosystems. The type, volume, and spatial distribution of LULC are regularly changing as the world's economic growth and resource exploitation progress, resulting in more than 30% of carbon output (Alawamy *et al.,* 2020). Policymakers must evaluate historical, current, and future LULC changes and the link between LULC changes and carbon storage changes. According to Houghton & Nassikas, (2017), Africa accounts for more than 17% of global carbon emissions from land use change. However, land use change contributes to 48% of total carbon emissions, increasing the atmospheric concentration of carbon dioxide to 400 ppm (Anokye *et al.,* 2021). This expected level has not been achieved (Siegert *et al.,* 2020) and continues to increase (Roser & Rodés-Guirao, 2013). Ecosystem services for tropical areas are considered sources rather than sinks of CO^2 since the timber in the savanna is harvested for energy and coal production (Tinlot, 2010). Therefore, it is most important to understand and quantify the dynamics of vegetation and carbon exchange. Several studies have addressed the topic of forest carbon stock assessments (Aabeyir *et al.,* 2020; Jucker *et al.,* 2022; Malhi *et al.,* 2021).

In Benin, researchers have conducted numerous studies on biomass models to quantify stock spatial distribution and historical emissions from deforestation, such as the works by Goussanou *et al.,* (2018), Houssoukpèvi *et al.,* (2022), Kora *et al.,* (2019), Soufouane *et al.,* (2022), and Chabi *et al.,* (2016). The impact of land use land cover (LULC) change on ecosystem services, including carbon stocks, is recognized as a significant threat to mountain areas, as stated by Moutouama *et al.,* (2020). However, the dynamics of LULC in the riverine area of Pendjari Reserve and the underlying change mechanisms among different LULC categories remain unclear, and there is a lack of long-term quantitative data for carbon storage valuation (Aitali *et al.,* 2022).

Accurate assessment of carbon budgets requires information on the spatial distribution of biomass and carbon stock, with aboveground biomass playing a crucial role (Balima *et al.,* 2020; Vahedi *et al.,* 2016). To assist low-carbon development, it is critical to anticipate future LULC changes under various development scenarios and assess related carbon storages based on credible data and techniques relevant to the Riverine region of Pendjari Reserve (Liu *et al.,* 2022). Various approaches and tools are employed for LULC modelling and carbon storage assessment, including LULC prediction models for simulating future scenarios (Muhammad *et al.,* 2022). Carbon storage assessment methods can be based on geophysical and chemical processes or geophysical methods of carbon density and land use land cover change.

The Integrated Valuation of Ecosystem Services (InVEST) model, developed by the Natural Capital Project of Stanford University, has demonstrated excellent performance in assessing large-scale carbon storage evaluations (Avtar *et al.,* 2022). This study aims to monitor and evaluate the carbon potential sequestration using the Markov-Chain and Invest model in the Riverine area of Pendjari Reserve. Specifically, the objective is to (i) assess land use land cover change from 1998 to 2020, (ii) evaluate land use change impact on carbon storage, and (iii) project carbon sequestration for the years 2035 and 2050.

6.2.Methods

6.2.1. Data collection

6.2.1.1, Land use land cover classification and projection

For this section, the methodology of Chapter 1 (Landsat images classification for the years 1998, 2007, 2013, and 2020 and land use projection for 2035 and 2050) was used.

6.2.1.2. Carbon pool sampling

Following a pre-survey in the study area, a random sample (West, 2016) was utilized to choose pilot sites based on community distribution. The snowball purposive sampling approach was used to select each pilot location. The research focused on the major communities of Berba, Gourmantche, and Wama, forming 55 %, 35 %, and 10 % of the entire study region, respectively. The proportionality technique was used to pick eight sites: four in Berba communities (Porga, Dassari, Kani, and Sepounga), two in Gourmantche communities (Sangou and Batia), and two mixed areas in Gourmantche and Wama communities. Five land use classes, namely wooded savannah, shrub savannah, cropland, fallow, and settlement, were selected for each site. Above ground, below ground, soil carbon, and dead wood were assessed. At each sampling location in the areas, a randomly selected 30 m x 30 m plot size was created to collect herbaceous plants, shrubs, seedlings, litter samples, and soil samples, and the Geographical Positioning System (GPS, WGS 84) coordinates of the plot's center and corners, as well as its elevation, was recorded. Because trees (including dead-standing trees) were sparsely dispersed across the research locations, a census of all trees in the pilot plots was conducted to eliminate mistakes in assessing tree biomass. With GPS, the complete pilot plot where the sample plot was placed was located. All of the trees in the tracked stories were recognized down to the species level, with a diameter tape and a Laser Rangefinder (TruPulse, 200) hypsometer (Measurement Devices Ltd. UK) used to measure height and the diameter at breast height (*dbh*) of 1.3 m above ground, respectively.

Similarly, in each of the 30 m ×30 m sample plots size, the diameter at 0.50 m (d0.50) aboveground and the height of shrubs were measured using a diameter tape or digital caliper and metal measuring tape, respectively. Three 1m^2 (1.0 m by 1.0 m) quadrats were laid out diagonally in the sample plot, one each close to the opposite corners and one at the centre of each plot. All the non-tree vegetation within the 1m^2 quadrat were severed at the base and immediately weighed with electronic weighing scale for fresh weight. Surface litter was also removed and weighed. Soil and roots samples were collected in a 1m^2 pit. Soil samples were taken at the following depths: 0–10 cm; 10–20 cm; 20–30 cm and 30-40 cm. The soil samples from same soil depth within a plot was thoroughly mixed in a large basin and subsamples of about 500 g collected for nutrient analysis. Corresponding soil samples were collected from the various soil depths with soil core samplers of known volume for bulk density determination. Only one set of bulk density samples will be taken per plot. All samples will be air dried.

6.2.2. Data analysis

6.2.2.1. Carbon estimation

The mean values of wood density (ρ) were extracted from the global wood density database by Zanne et al. (2009) using the R package 'BIOMASS' developed by Réjou-(Méchain *et al.,* 2017). The assigned values were at the species or genus level. The volumes were combined using a Microsoft (MS) Excel Pivot Table based on different tree species. The average density of all the samples for each tree species was calculated as their wood density (ρ). We multiplied the wood density by the volume to determine the dry mass. Consequently, the sum of the masses of the individual logs was used to calculate the overall mass of each tree. Aboveground mass (AG_M) of the individual trees was obtained from the *dbh*, height and wood density of the various tree species by the model of Aabeyir *et al.* (2020) as:

$$ABM = 0.0580\rho((dbh)^2 H)^{0.999} \quad [6.\ 1]$$

6.2.2.2. Laboratory methods

The soil samples were be air-dried, processed to remove visible plant residue and then sieved through 2mm mesh for chemical and physical analyses. Soil texture measurements were be performed on soil from one pit per site on the various soil depths. Soil bulk density (SBD) was be determined by the volumetric ring method (Hounkpatin *et al.,* 2022a). Bulk density measurements were be performed by oven-drying the soil samples at 105 ºC for 48 hours, and then reweighed for dry weight determination (Hounkpatin *et al.,* 2022b). Total soil C concentration was determined by dry combustion (Nottingham *et al.,* 2020) in a CH Shimadzu analyser. The sieved soil samples were soaked in 10% HCl to remove any carbonates from the soil and then oven-dried at 45 ºC to constant eight. The soils were then ground and analyzed for carbon content using a Carlo Erba elemental analyzer. The elemental analysis was repeated three times and the average C values used in the analysis. Soil carbon stock (SCS, Mg C ha-1) was estimated as (e.g., Adu-Bredu *et al.,* 2021) as (Equation 6.2);

$$SCS = SOC \times BD \times D_P \quad (6.2)$$

Where SOC is soil carbon content (%), BD is soil bulk density (g cm^{-3}) and D_P is soil depth (m) was calculated by multiplying the soil concentrations by the bulk density. The biomass of the non-tree vegetation (H_b) and ground litter (L_b) carbon stock (Mg C ha^{-1}) per plot was estimated (Adu-Bredu et al., 2021) as (Equation 6.3);

$$H_b \text{ or } L_b = \frac{1}{n}\sum_1^n D_m \times \frac{10000}{A} \times CFr \quad (6.3)$$

Where n is number of quadrats per plot, D_m is dry mass of non-tree vegetation or litter, A is area of the quadrat (m^2) and CFr is carbon fraction of the litter or non-tree vegetation.

6.2.2.3. *Assessment of carbon storage InVEST model*

According to (Pechanec *et al.,* 2018), the initial data necessary for running the InVEST carbon storage and sequestration model were LULC data from the research region and carbon density data from each LULC.

The carbon sequestration map in the InVEST model was created using the LULC map for the current year (2020) and the projected years (2035 and 2050). A carbon pool table was created using the FSI report and IPCC 2006 criteria and a literature analysis to indicate the carbon pool in aboveground biomass, belowground biomass, soil organic carbon, and deadwood carbon in different classes of LULC maps. The InVEST carbon model simply tracks the carbon cycle, estimating the total amount of carbon stored in the whole research region by aggregating carbon pool values assigned to each LULC type (Kim *et al.,* 2018).

According to the model, the carbon density of each LULC type (i) is as shown in Equation (6.4):

$$Ci = Ci\ (above) + Ci\ (below) + Ci\ (dead) + Ci\ (soil) \qquad (6.4)$$

Where Ci (above), Ci (below), Ci (dead) and Ci (soil) are the carbon density of aboveground biomass, belowground biomass, dead organic materials and soil carbon density (Mg C ha^{-1}), in the *i*th LULC type, respectively. The total carbon dioxide storage equivalent (CO_2e) of the study area is then calculated by the model software based on Equation 6.5 as;

$$CO_2\mathrm{e} = \sum_i^n (Ci \times A_i \times \tfrac{44}{12}) \qquad (6.5)$$

where *n* is the number of LULC types in the study area, and *A*i (ha) is the area of each LULC types. The value of the carbon benefit (REDD+ revenue) is obtained by multiplying the CO_2e from the computation by unit price from REDD+ projects in the voluntary carbon markets. The unit price, which is US$ 4.20, was calculated from the average of the unit price of REDD+ project types transaction in the voluntary carbon market for three years of 2019, 2020 and 2021 at US$3.90, US$4.30 and US$4.40 (Donofrio *et al.,* 2021). The value was discounted by 10% using the Market discount price (Gittinger, 1982, Bank World 1996).

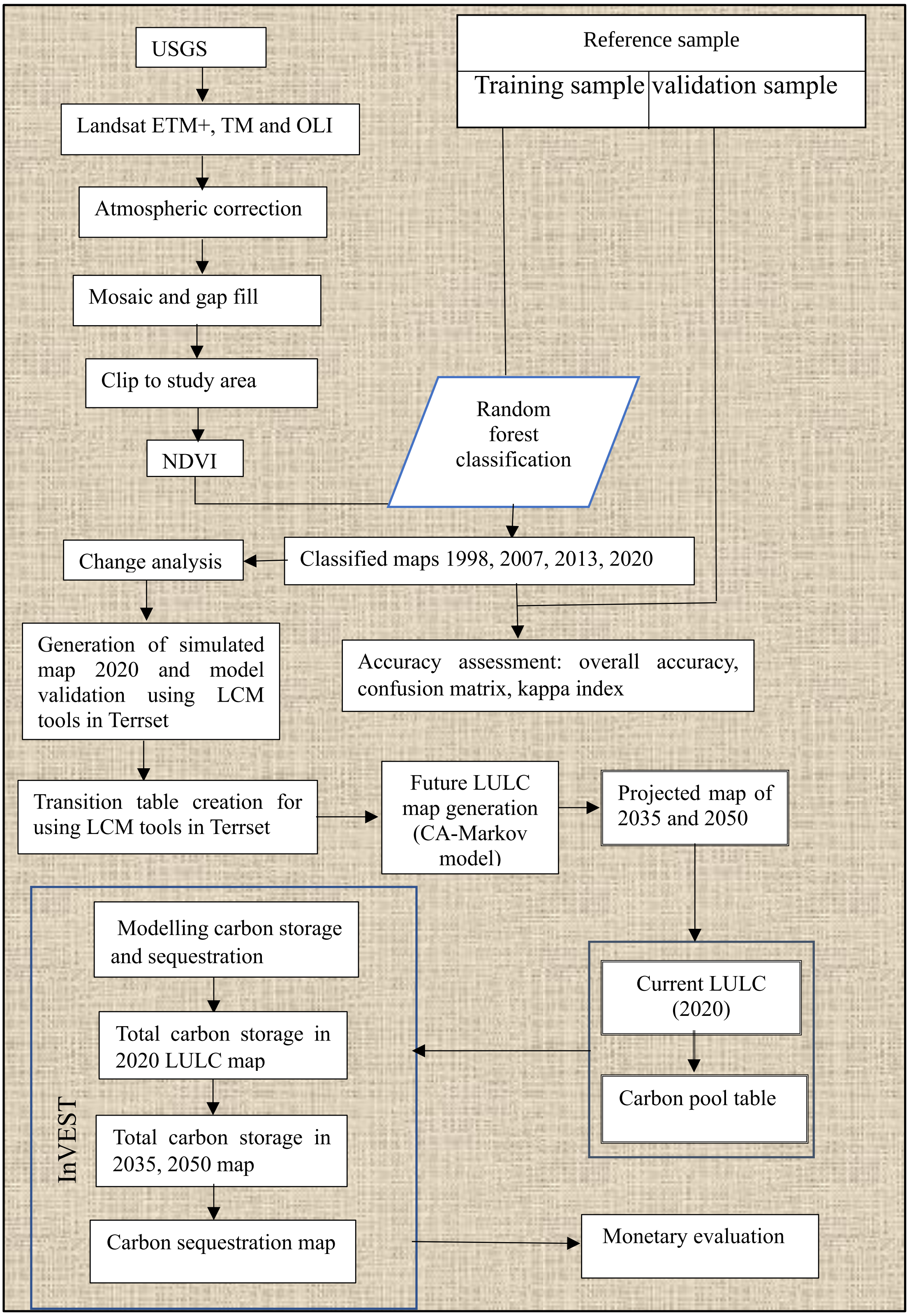

Figure 6.1. Methodology steps followed for carbon store and monetary evaluation.

6.3. Results

6.3.1. Prediction of carbon sequestration and valuation

6.3.1.1. Carbon pools table

One of the most crucial inputs to the Invest model is data from the carbon pools table. Tables (6.1) and (6.2) show the findings of wood density per tree species and carbon pool per land use types. From the Table 6.2, the highest estimated aboveground carbon pool value was found in wooded savannah (595,15 Mg C ha^{-1}) followed by fallow (161.152 Mg C ha^{-1}), shrub savannah (146.42 Mg C ha^{-1}), cropland (138.57 Mg C ha^{-1}), and settlement (17 Mg C ha^{-1}). The estimated belowground carbon values of wooded savannah was 98.146 (Mg C ha^{-1}), and the corresponding value for shrub savannah, fallow and settlement was 50.00. 30.94, 27.08 and 4.25 Mg C ha^{-1}, respectively. However, fallow and settlement have the highest value of carbon stored in the soil was found in the fallow, followed in a decreasing order by settlement, forest, shrub savannah and cropland, with the value of 69.14, 68.76, 65.11, 64.26 and 62.72 Mg C ha^{-1}, respectively. The highest estimated carbon stock of dead wood was observed in the wooded savannah, followed by cropland, shrub savannah, fallow and settlement with the value of 0.57, 0.49, 0.46, 0.40, and 0.32 Mg C ha^{-1}, respectively.

Table 6.1Average wood density per tree species.

Number	Genus	Wood density	Number of tree
1	*Adansonia digitata*	0.276	1
2	*Gymnospora senegalinsis*	0.578	45
3	*Vitellaria paradoxa*	0.578	45
4	*Acacia gourmaensis*	0.749	1
5	*Acacia macrostachya*	0.749	1
6	*Afzelia africana*	0.693	14
7	*Albizia lebbeck*	0.554	11
8	*Anarcadium occidentale*	0.578	45

9	*Anogeisus leiocarpus*	0.578	45
10	*Azadirachta indica*	0.578	45
11	*Balanites aegyptiaca*	0.667	2
12	*Bligia sapida*	0.578	45
13	*Bombax costatum*	0.374	3
14	*Brewia bicolor*	0.578	45
14	*Bridelia ferruginea*	0.528	3
15	*Burkea africana*	0.647	3
16	*Cassia siberiana*	0.738	2
17	*Ceiba pentadra*	0.281	1
18	*Combretum collinum*	0.915	2
19	*Combretum molle*	0.915	2
20	*Combretum nigricans*	0.915	2
21	*Commiphora pedunculata*	0.578	45
22	*Crotalaria retusa*	0.578	45
23	*Delonix regia*	0.534	2
24	*Detarium macroscapium*	0.71	1
25	*Dichrostachys cinera*	0.578	45
26	*Diospyros mespiliformis*	0.702	3
27	*Dombeya quinqueseta*	0.482	1
28	*Elaeis guineensis*	0.578	45
29	*Entada africana*	0.578	45
30	*Erythrina senegalensis*	0.479	2
31	*Eucalyptus camadulensis*	0.578	45
32	*Fadogia agrestis*	0.578	45
33	*Ficus glumosa*	0.45	4
34	*Ficus trichopoda*	0.45	4
35	*Ficus villis*	0.45	4
36	*Gardenia aquala*	0.578	45
37	*Gmelina arborea*	0.423	6
38	*Grewia bicolor*	0.426	2
39	*Gymnospora senegalensis*	0.578	45
40	*Iphanea tebeica*	0.578	45
41	*Isoberlinia doka*	0.627	2
42	*Jatrpha curcas*	0.578	45
43	*Kaya senegalensis*	0.578	45
44	*Lannea accida*	0.405	1
45	*Lannea microcarpa*	0.405	1
46	*Leptadenia hasta*	0.578	45
47	*Lonchocarpus laxiflorus*	0.578	45
48	*Manguifera indica*	0.578	45
49	*Moringa oleifera*	0.578	45
50	*Opillia celtidifolia*	0.578	45
51	*Parinari congensis*	0.74	4
52	*Parkia biglobosa*	0.525	1

53	*Prosopis africana*	0.879	2
54	*Pseudocedrela kotschyi*	0.621	1
55	*Ptelopsis suberosa*	0.578	45
56	*Pterocarpus erinaceus*	0.74	1
57	*Rourea coccinea*	0.578	45
58	*Sarcocephalus latifolius*	0.578	45
60	*Strychnos spinosa*	0.718	2
61	*Tamarindus indica*	0.854	3
62	*Tectona grandis*	0.601	33
63	*Terminalia superba*	0.459	57
64	*Trichilia emetica*	0.498	1
65	*Vitex doniana*	0.4	1

Table 6.2.Carbon pools for different land use types

LULC name	C_above	C_below	C_soil	C_dead
Wooded savannah	595.15	98.146	65.11	0.57
Shrub savannah	146.42	50.80	64.26	0.46
Cropland	138.57	27.076	62.72	0.49
Fallow	161.152	30.94	69.14	0.4
Settlement	17.00	4.25	68.76	0.32

6.3.1.2. Carbon stored in 2020 and projected 2035 and 2050 land use

The total carbon stored in current land and projected future land use is shown in Figures 6.4 to 6.6. Analyzing these figures reveals that the carbon store per land-use class remains constant from the current year, 2020, to the projected years, 2035 and 2050. The carbon stock in each grid cell aligns with the map for 2020 and years 2035 and 2050. Negative values show carbon emitted into the atmosphere and positive values signify carbon sequestration. Notably, the wooded savannah area contains the highest carbon value (ranging from 23.468 to 68.308 Mg C) per grid cell, followed by the shrub savannah area (20.400-23.468 Mg C). Cropland contains 8.1288 to 20.400 Mg C of carbon, while settlements exhibit a lesser amount of carbon, with 8.12288 Mg C per grid cell.

The spatial distribution of current and future carbon sequestration in the riverine area of Pendjari Reserve is influenced by the existing landscape. The sequestration raster (Figures 3.5 and 3.7) illustrates the difference in stored carbon between future and current land cover. The results of the sequestration raster (Figure 6.5) indicate negative values (-60.18 Mg C to -44.95 Mg C and -44.95 Mg C to 2.86 Mg C) in the significant parts of the study area (wooded savannah and settlement), while some areas (shrub savannah, cropland, and fallow) display positive values (2.86 Mg C to 15.13 Mg C and 15.13 Mg C to 47.71 Mg C). Conversely, the sequestration raster results (Figure 6.7) indicate positive values (15.34 Mg C to 60.17 Mg C and 2.6 Mg C to 15.34 Mg C) in the predominant parts of the study area (wooded savannah and shrub savannah), while a few areas (cropland, fallow, and settlement) show negative values (-60.18 Mg C, -60.18 Mg C to -45.08 Mg C, and -45.08 Mg C to 2.86 Mg C).

The results highlight that wooded savannah and shrub savannah classes store the highest amount of carbon. The statistics (Table 6.3) demonstrate that wooded savannah exhibits the maximum carbon storage in 2050 (494,198.1 Mg C), with a decrease in 2020 and 2035 with the value of (387,059.4 Mg C and 387,047.2 Mg C, respectively). For shrub savannah, the lowest value (154,658.2 Mg C) is observed in 2020, the highest value (156,466.1 Mg C) in 2050, and the medium value (154,740.2 Mg C) in 2035. Conversely, cropland, fallow, and settlement display the lowest stored carbon values.

In terms of carbon sequestration, the total results (Table 6.4) indicate that the most significant carbon sequestration (50,893.4 Mg) occurs from 2035-2050, while the lowest value (798.12 Mg) is observed from 2020-2035 over fifteen years. The highest gain and loss of carbon sequestration occur from 2035-2050, with 108,878 Mg and -

57,984.6 Mg, respectively. Conversely, the lowest gain and loss are observed from 2020-2035, with 845.56 Mg and -47.52 Mg, respectively.

Table 6.3.Carbon stored (Mg) in different LULC types for 2020, 2035 and 2050.

Land use type	Carbon / pixel	Area (ha) 2020	Total carbon 2020	Area (ha) 2035	Total carbon 2035	Area (ha) 2050	Total carbon 2050
Wooded savannah	68	63245	387059.4	63243	387047.2	80751.33	494198.1
Shrub savannah	24	71601	154658.2	71639	154740.2	72438.03	156466.1
Cropland	21	32026	60529.14	32038	60551.82	13729.31	25948.39
Fallow	21	2936.07	61657.47	2971.35	62398.35	1857.96	39017.16
settlement	8	2007	1445.04	1958	1409.76	1959.746	1411.017
Total			665349.2		666147.4		678023.6

Table 6.4.Carbon sequestration (Mg) in different LULC types for 2020 -2035 and 2035-2050

Land use type	Carbon sequestered 2020-2035 Mg	Carbon sequestered 2035-2050
Wooded savannah	-12.24	1,725.9
Shrub savannah	82.08	107,150.9
Cropland	22.68	-34,603.4
Fallow	740.88	-23,381.2
Settlement	-35.28	1.2
Total	798.12	50,893.4

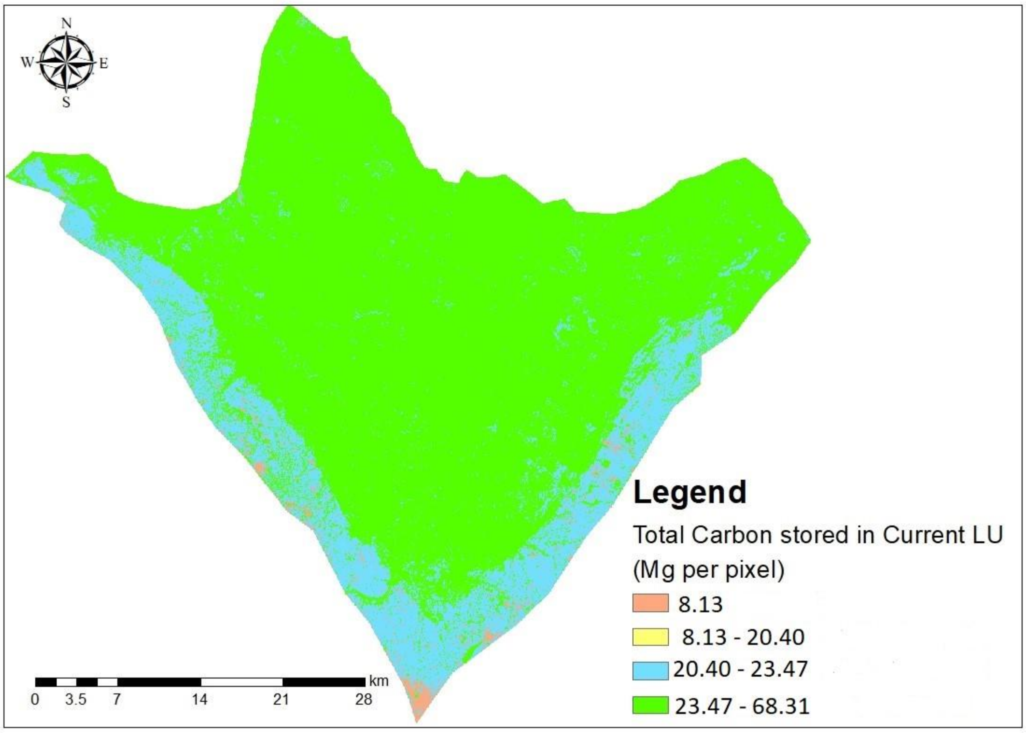

Figure 6.2.Total carbon storage in 2020

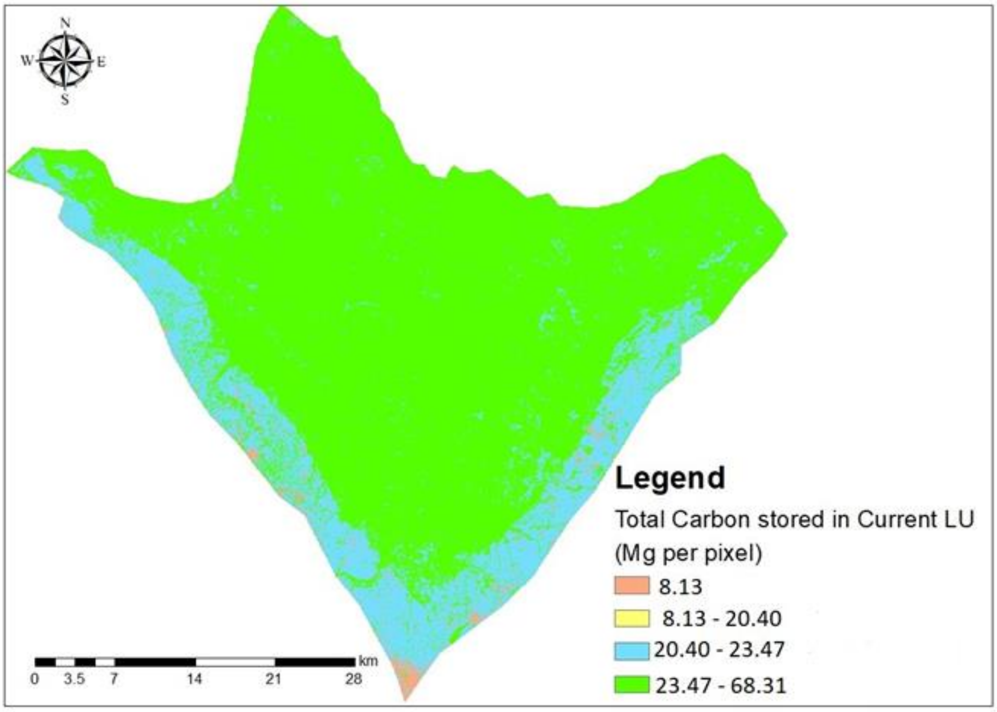

Figure 6.3.Total carbon stored in future (2035)

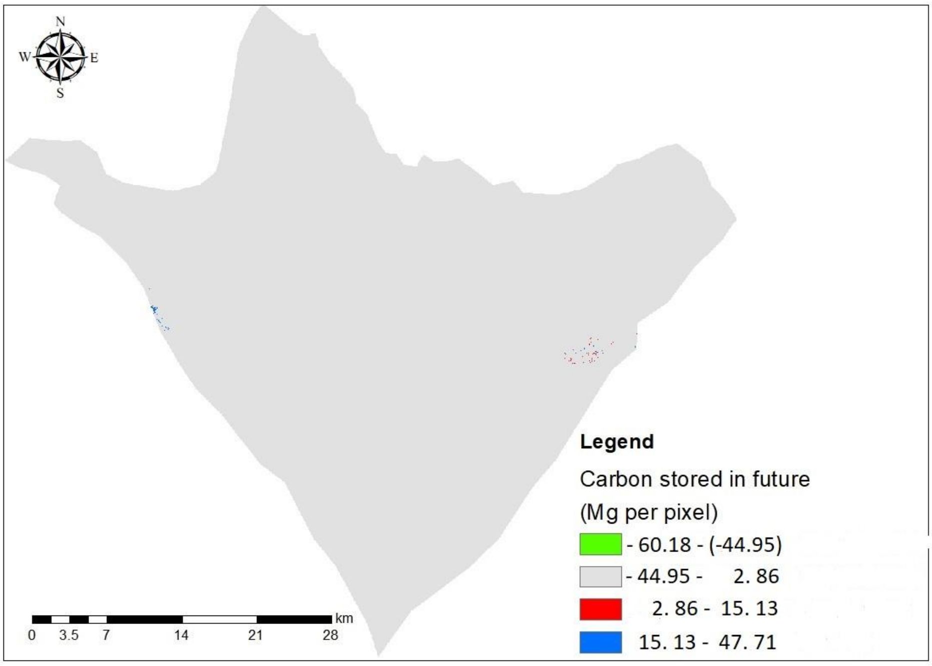

Figure 6.4. Change in carbon stored in 2020 – 2035

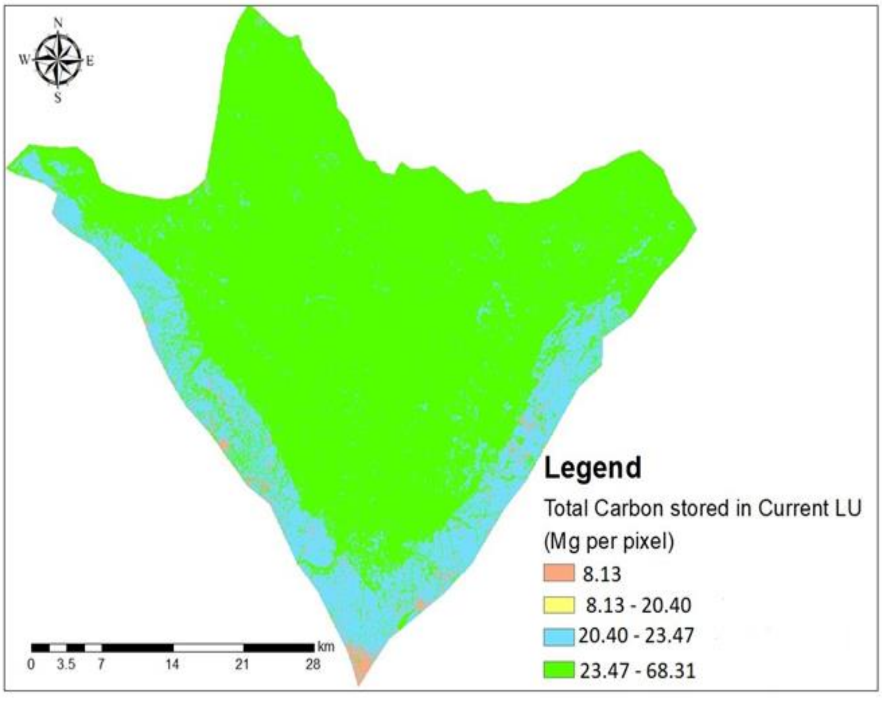

Figure 6.5.Total carbon stored in 2050

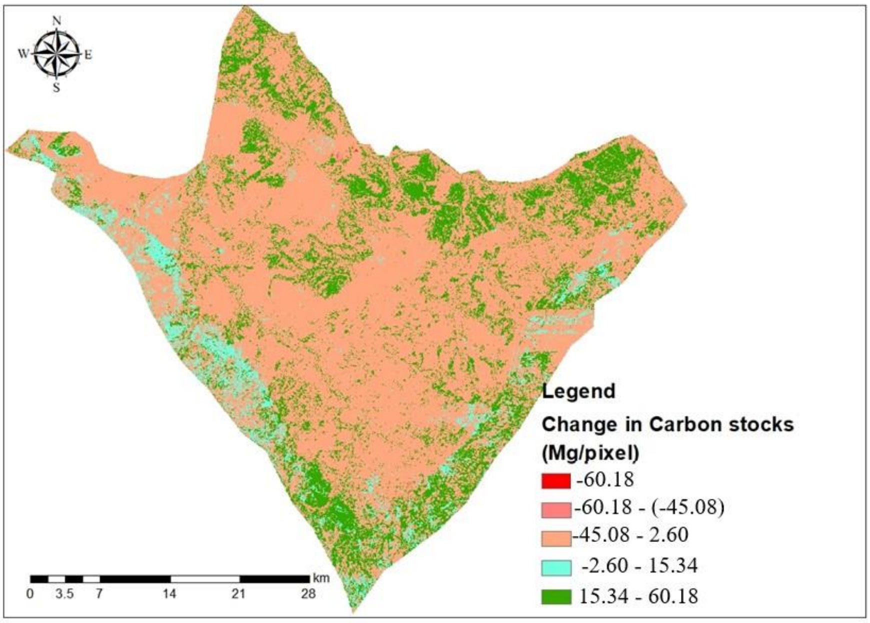

Figure 6.6.Changes in carbon stored in 2020-2050

6.3.1.3. Monetary Valuation of Carbon Storage and Sequestration

Using economic data, the simulation produced a raster representing the economic value per pixel of sequestered carbon in the future scenarios (see Figures 6.7 and 6.8). Analyzing the spatial distribution of the economic value, it is evident that certain areas in the study region exhibit negative values, indicating a lack of carbon sequestration capacity. Consequently, the projected results indicate an economic loss, reflected in a negative Net Present Value (NPV) in US$. However, the smallest part of the study area can clump with positive values with the highest capacity of sequestering carbon. This is shown by the projected economic gain indicating a positive value in Net Present value (NPV) US$ 17.1067 to 90.431; and US$ 90.431 to 285.121 US$ for the same period (Figure 6.7). According to Figure (6.8) the most important of the area study is grouped with positive values with the highest capacity of sequestering carbon, indicating the economic gain which was projected in Net Present Value (NPV) US$ 7.785 to 46.006 and US$ 46.006 to 180.485. In contrast, the smallest part is grouped with negative values with the negative capacity of carbon sequestering, showing the economic loss which was projected in Net Present Value (NPV) US$ -180.485; US$-180.485 to -135.187 and -135.187 to – 7.785. The total monetary value of carbon sequestration within the riverine area of Pendjari reserve was estimated at 3,352.104 US$ per 15 years (2020-2035) and 213,752.3 US$ per 15 years (2035-2050). For the same period, the economic value of carbon sequestration loss was estimated at 199.584 US$ and 243535.3 US$.

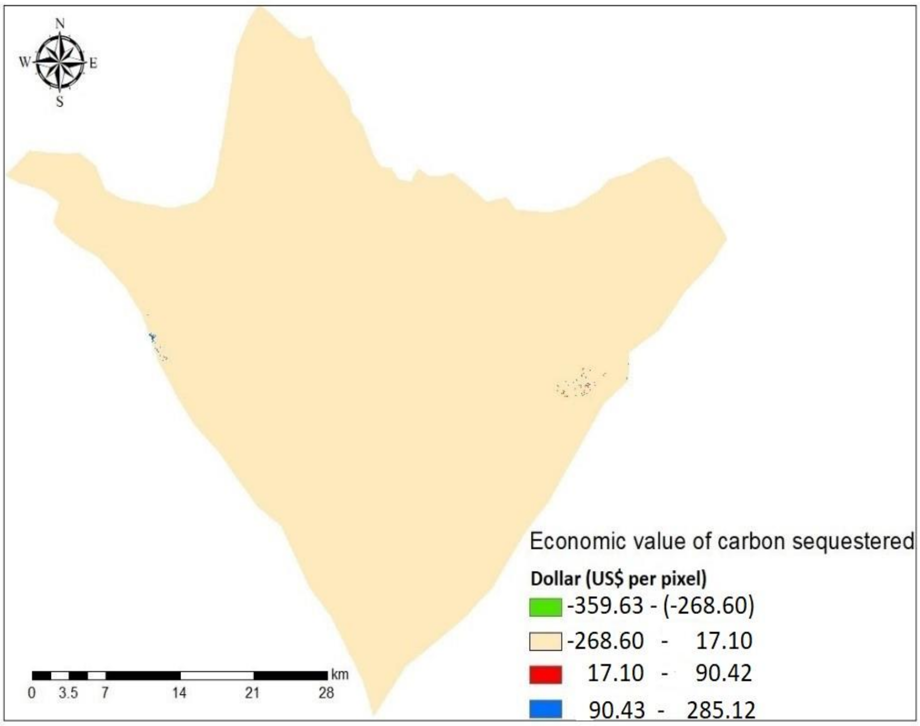

Figure 6.7.Monetary value of carbon sequestered in 2035

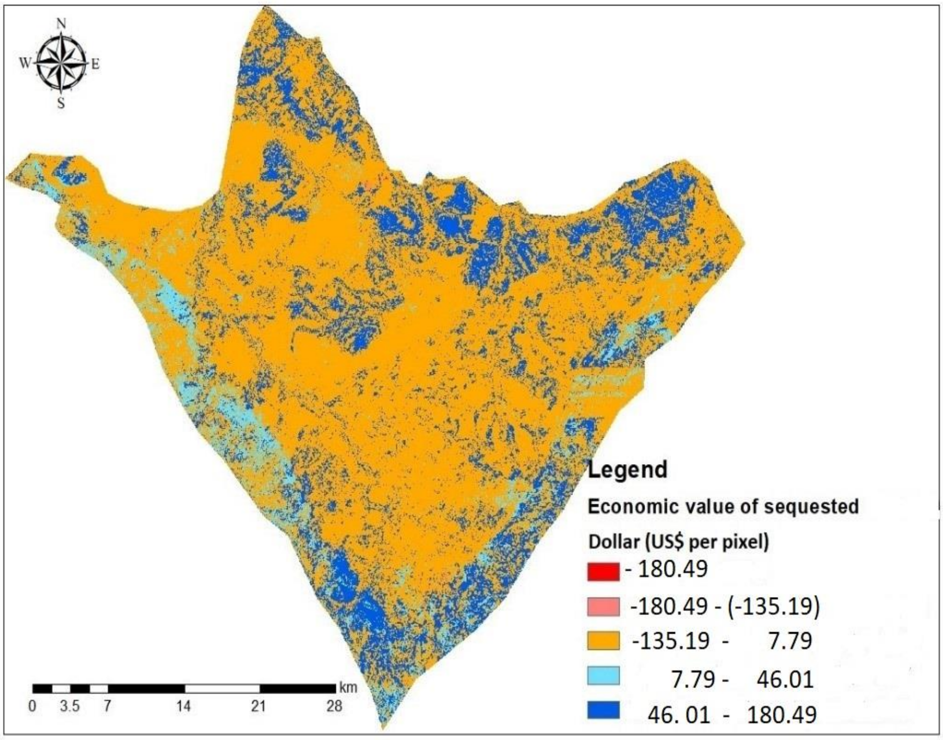

Figure 6.8.Monetary value of carbon sequestered in 2050

6.4. Discussion

The analysis of carbon pool results in Table 6.2 reveals notable differences in aboveground and belowground carbon among various land-use and land-cover (LULC) types, while soil carbon exhibits comparatively less variation. The highest estimated aboveground carbon pool is observed in wooded savannah (595.15 Mg ha-1), followed by fallow (161.152 Mg ha-1) and shrub savannah (146.4 Mg ha-1). Cropland (138.57 Mg ha-1) and settlement (17 Mg ha-1) exhibit the lowest carbon densities. Similar findings were reported by Kumarasiri et al. (2022), who noted lower carbon density in industrial and agricultural areas, as well as home gardens. The aboveground carbon pool values reflect the direct relationship between woody materials and aboveground carbon storage in the study area (Damnyag et al., 2011). Likewise, belowground carbon values exhibit a similar pattern to aboveground carbon, with significant variation among different LULC types. In contrast, soil and litter carbon show less pronounced variations. Due to the unavailability of dead wood data, this study only considers litter carbon. Similar challenges were faced by Paquit and Mindana (2017), who also focused solely on litter carbon due to difficulties in accurately assessing deadwood carbon in the field. This challenge arises from uncertainties in carbon transport between litter, deadwood, and soil. Detecting changes in ecosystem services (ES) associated with LULC change is crucial for understanding how the quality and quantity of services are affected by human activities. Local and regional assessments are urgently needed to inform appropriate policies that enhance human well-being, as adverse LULC change can have severe impacts on ecological processes and community livelihoods (Tolessa *et al.,* 2017). Consequently, effective land management and implementation of ES schemes to support biodiversity conservation and community livelihoods should be based on accurate assessments of ES within the area.

Invest model is used to simulate carbon sequestration for three scenarios present (2020), future (2035), and (2050) land use land cover change classes. The spatial distribution of carbon stocks, assessed with Invest model, indicated values ranging from 8.12 to -68.308 Mg C per pixel, depending on the different LULC types. As shown in the results in Table 6.3, with a land area of 168892.38 ha, the riverine area of Pendjari reserve currently stores 2,009,520 Mg C, whereas carbon storage varies with land use types. The wooded savannah obtained the most considerable Carbon stored, 387,059.4 Mg C in 2020 decreased to 12.4 Mg C in 2035 and increased to 107,151.1 Mg C in 2050, comprising 58.17%, 58.10%, and 68.92%. Furthermore, it is indicated that shrub savannah has captured a considerable amount of carbon, 154,658.2 Mg C in 2020, and increased by 81.8 Mg C and 1726.1 Mg C respectively, in 2035 and 2050, which comprise 23.24%, 23.22%, and 21.82%. However, fallow land accounted for 61,657.47 Mg C in 2020 and increased by 740.93 Mg C in 2035 with 9.266% and 9.367%, but the carbon stored decreased to 23381.24 Mg C with 3.925648%. Moreover, it is revealed that cropland held 60529.14 Mg C in 2020, increased by 22.66 Mg C in 2035, and decreased to 34603.41 Mg C in 2050 with respectively 9.097%, 9.089%, and 3.618%. The settlement captured the lowest amount of carbon with 1445.05 Mg C in 2020, and it decreased to 35.29 Mg C in 2035 and increased by 1.26 Mg C in 2050. This result is confirmed by (Chacko *et al.,* 2018; Kumarasiri *et al.,* 2022) in Sri Lanka Uva Province, who found that vegetative land use types stored relatively more carbon than other land use types.

The total monetary value of carbon sequestration within the riverine area of Pendjari reserve was estimated at 2.234.736 US$ per year from (2020-2035); and 14,250.15 US$ per year from (2035-2050). For the same period, the economic value of carbon loss was estimated at 13.3056 US$; and 16,235.69 US$. The fallow recorded the most important economic value of 3,111.696 US$, followed by shrub land 344.736 US$, and cropland obtained 95.256 US$. Still, the settlement recorded the most important loss of value of 148.176 US$ and wooded savannah loss of 51.408 US$ from (2020-2035). Moreover, the lowest economic value of carbon sequestration has recorded in the settlement area of 5.04 US$, the highest value has found in shrub savannah 450,033.8 US$, followed by wooded savannahs 7,248.78 US$. At the same time, the cropland and fallow lost the most important value respectively with 145,334 US$ and 98,201 US$. The discount rate and social value parameters have considered in order to understand the net present value of carbon sequestered in each period (2020-2035), and (2035-2050). The same approach was used by (Boyland, 2006) who used discount rate to elaborate the time value for carbon sequestration to calculate its net present value.

6.5. Conclusions

This study investigates LULC effects on carbon storage and valuation in riverine area of Pendjari in Benin. The Invest model was found to be suitable for carbon storage and sequestration assessment and can be used as an important tool to evaluate the total carbon storage in different types of LULC. Moreover, this model can be used in the detection of carbon potential for area REED+ or mapping spatial distribution of carbon storage. The most important land use, which stores the highest amount of carbon is the wooded savannah, followed by the fallow land-use. The carbon stock mapping in different LULC highlights the effectiveness of vegetation pattern in land use types, and how much carbon lost over the time due to anthropogenic activities causes changes in land use. Carbon sequestration and valuation are considered as the main tool for decision making process, such as environmental planning and policies regarding ecosystems services management. Provision of information about carbon stock can therefore contribute to development through carbon credit promotion and help to better understand climate change at country level.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1. Conclusions

This chapter presents the conclusions and recommendations based on the main findings of the study and discussions from the previous chapters.

What is the county-level LULC patterns in the riverine area of Pendjari Reserve from 1998 to 2020?

Land use is the main factor which contributed to ecosystem services degradation and affected negatively human wellbeing. The research shows that land use is changing and affecting mainly Wooded savannah which is decreased by 4.7 % during 1998-2007, while continuous declines of 8 % and 11.5 % occurred respectively during 2007-2013 and 2013-2020. The area of shrub savannah increased by 10.5 % from 1998-2007 and 3.88 % during 2007-2013, while an apparent decline in the shrub savannah was observed by 1.17 %. The two main factors negatively affecting ecosystems of the study area are human activities and climate change. From 1998-2007, the decline in cropland was documented by 6.66 %, while an evident increase was observed by 4.33% and 11.1 % respectively from 2007-2013 and 2013-2020. Specifically, the fallow land is released by 0.77 % from 1998-2007, before decreasing by 0.7 % and increasing by 0.83 % respectively from 2007-2013 and 2013-2020. The results of predicted and simulation showed small reduction of wooded savannah area, however the most important reduction would be observed in settlement.

Why do farmers use the preferred tree species in the agroforestry system?

As shown in this study, farmers' choice for tree and crops association in agroforestry system as an adaption strategy to climate change was influenced by and accessibility (landownership), farm size, district and interaction between landholding and farm size. The most important agroforestry system was agrosilvicultural which promoted the association of local tree species with staple food crops. The main agroforestry trees are *Vitellaria paradoxa, Parkia biglobosa* and *Lannea microcarpa*. Farmers in the study area prefer a combination of crops and trees in their agroforestry systems to adapt to climate change, and the inclusion of trees has a positive impact on crop production by reducing the negative effects of climate variability. However, tree-crops associations were mostly influenced by ethnic group. This study showed that the agroforestry system conserved endangered species (*Pterocarpus erinaceus)* and vulnerable species *(Khaya senegalensis, Afzelia africana and Vitellaria paradoxa)*.

Do climate change and tree conservation affect Crop yield in agroforestry systems?

Climate variability impact on crop yield is mainly dependent on the crop species. The findings showed that cool season species will be more affected because of increase in average temperature**.** The hottest daily and monthly mean daily minimum temperature trend have significant influence on crop yield. However, the mean annual difference between daily maximum and minimum temperature influence negatively and significantly crop yield. Results showed increasing pattern of annual rainfall and growing degree days. Results indicate that the lowest temperature positively and considerably impacted maize, while maximum temperature and relative humidity adversely affected maize. The minimum temperature had a positive and substantial impact on sorghum. The lowest temperature positively impacted cotton yield but was negatively affected by mean temperature and relative humidity. Maximum temperature and relative humidity positively and significantly impacted cowpea growth. The results indicated that crop yield was influenced by tree species and tree proximities. The crop yield variation observed under agroforestry species was related to soil nutrients availability.

How does carbon potential sequestration vary in agroforestry systems?

The study shows LULC impacts on carbon storage and valuation in riverine area of Pendjari in Benin. The study indicates that Invest model is suitable for carbon storage and sequestration assessment and can be used as an important tool to evaluate the total carbon storage in different types of LULC. The study shows that the most important land which embraces the effectiveness amount of carbon stored is wooded savannah. Shrub savannah had the highest and fallow had the second-highest stored carbon. A significant concern to the sustainable supply of ES and to the reduction of trade-offs in land use decision making is the rapid alteration of the land system in the study area. The modelling of the potential of carbon sequestration in agroforestry systems indicates that they have a significant potential for mitigating climate change by sequestering carbon. Therefore, promoting agroforestry systems in the area can provide a sustainable solution for enhancing agroecosystem services provisioning and mitigating climate change.

7.2. Recommendations

For Policy

- ✓ Existing efforts for conservation and restoration should be maintained
- ✓ Given the importance of agroforestry systems for farmers livelihoods, this practice should be promoted
- ✓ Policy helps farmers to adopt tolerant crops to high temperature and early-maturing crop varieties

For Researchers

Furthermore, researchers should work to improve carbon eestimation models by incorporating additional variables such as soil type, land management practices, and climate variability.

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APPENDICES

Appendice 1: Discriminants analysis and V test on crops and trees species and services with ethnic

Variables discriminants	V test	category		Overall		Prob
		Me	Sd	Me	Sd	
1						
Afzelia africana	2.07	0.10	0.56	0.11	0.61	0.038
Combretum aculeatum	2.72	0.01	0.09	0.01	0.10	0.007
Diospros mespiliformis	2.97	0.12	0.48	0.13	0.50	0.003
Balanites aegyptica	4.53	0.12	0.51	0.14	0.54	0.000
Leptadernia hastata	-5.86	0.07	0.49	0.10	0.60	0.000
Sarcocephalus latifolus	-8.39	0.01	0.14	0.03	0.18	0.000
Dichrostachys cinera	-10.82	0.00	0.05	0.05	0.46	0.000
Trichilia emetica	-13.14	0.11	0.54	0.29	1.51	0.000
Pseudocedrela kotschyi	-13.32	0.00	0.00	0.01	0.12	0.000
Daniellia oliveri	-16.64	0.01	0.11	0,05	0,28	0.000
2						
Dichrostachys cinera	17.28	4.00	1.73	0.05	0.46	0.000
Vitellaria paradoxa	14.04	2.00	0.00	0.05	0.28	0.000
Lannea microcarpa	9.69	3.00	1.73	0.10	0.60	0.000
Diospros mespiliformis	5.45	1.50	0.87	0.13	0.50	0.000
Afzelia.africana1	3.78	1.25	2.17	0.11	0.61	0.000
Pterocarpus erinaceus	2.26	0.75	0.43	0.16	0.53	0.024
Parkia biglobosa	2.14	6.00	3.46	2.34	3.44	0.032
Lannea microcarpa	2.1	4.00	3.75	2.56	0.92	0.005
3						
Pseudocedrela kotschyi	17.30	0.83	0.37	0.01	0.12	0.000
Trichilia emetica	17.18	10.83	2.79	0.29	1.51	0.000
Sarcocephalus latifolus	11.03	0.83	0.37	0.03	0.18	0.000
Daniellia oliveri	9.87	1.17	0.37	0.05	0.28	0.000
Balanites aegyptica	6.25	1.50	0.50	0.14	0.54	0.000
Combretum aculeatum	3.67	0.17	0.37	0.01	0.10	0.000
Combretum collinum	2.04	0.50	0.50	0.10	0.48	0.041
Vitellaria Paradoxa	-2.13	1.67	0.47	11.59	11.50	0.033

Variables discriminants	Cla/Mod	Mod/Cla	Global	V test	P value
1					
Ethnie=Gourmantche	100.00	46.44	45.15	3.06	0.002
ZeamaysVignaungunlata=yes	98.15	90.88	90.03	2.49	0.013
ZeamaysGlycine max=yes	97.74	98.58	98.06	2.46	0.014
Zea maysVignasubterranea =yes	97.73	98.29	97.78	2.35	0.019
SorghumbicolorVignaunguiculata= yes	97.50	100.00	99.72	2.20	0.028
Gossypiumhirsutumvignahirsutum	0.00	0.00	0.28	-2.20	0.028
Sorghum bicolor=no	0.00	0.00	0.28	-2.20	0.028
Zeamays =no	75.00	1.71	2.22	-2.35	0.019
Vigna unguiculata = yes	88.89	9.12	9.97	-2.49	0.013
Gossypium hirsutum=yes	94.44	48.43	49.86	-3.34	0.001
2					
Ethnie = Berba	11.11	100.00	9.97	3.93	0.000
Gossypium hirsutum = yes	6.06	100.00	18.28	3.28	0.001
ZeamaysGlycine max=yes	100.00	25.00	0.28	2.54	0.011
Sesamumindicumcajanuscajan=yes	33.33	25.00	0.83	2.13	0.033
Zea maysGlycine max=yes	0.56	50.00	98.06	-3.10	0.002
SesamumindicumArachishypogea= yes	0.00	0.00	81.72	-3.28	0.001
ArachishypogeaZeamays=No	0.00	0.00	90.03	-3.93	0.000
3					
Ethnie =Wama	25.00	33.33	2.22	2.73	0.006
Sorghum bicolor = yes	3.33	100.00	49.86	2.44	0.015
Oryza sativa = yes	100.00	16.67	0.28	2.39	0.017
Zea mays..*Vignaungulata*=no	0.00	0.00	45.15	-2.22	0.026
Gossypium hirsutum..Vignasubte =No	1.39	83.33	99.72	-2.39	0.017
Zea mays..Glycine max =No	1.13	66.67	97.78	-2.73	0.006

Appendice 2. Trends in SPI and SPEI

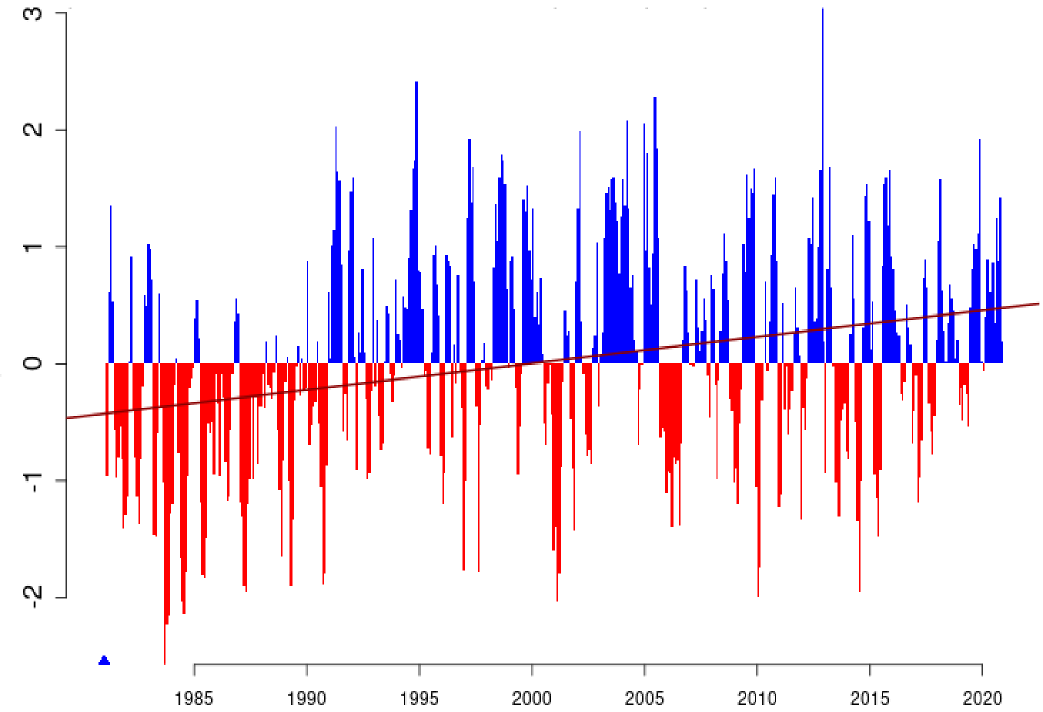

Figure1. Standardized precipitation Evapotranspiration (SPEI3)

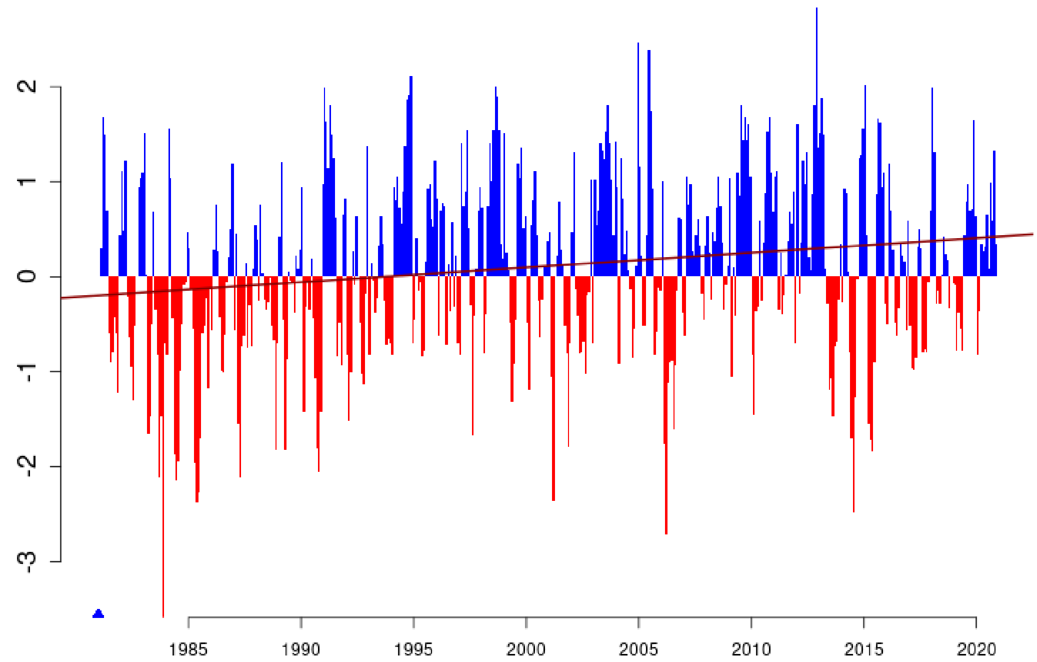

Figure2. Standardised precipitation (SPI3)

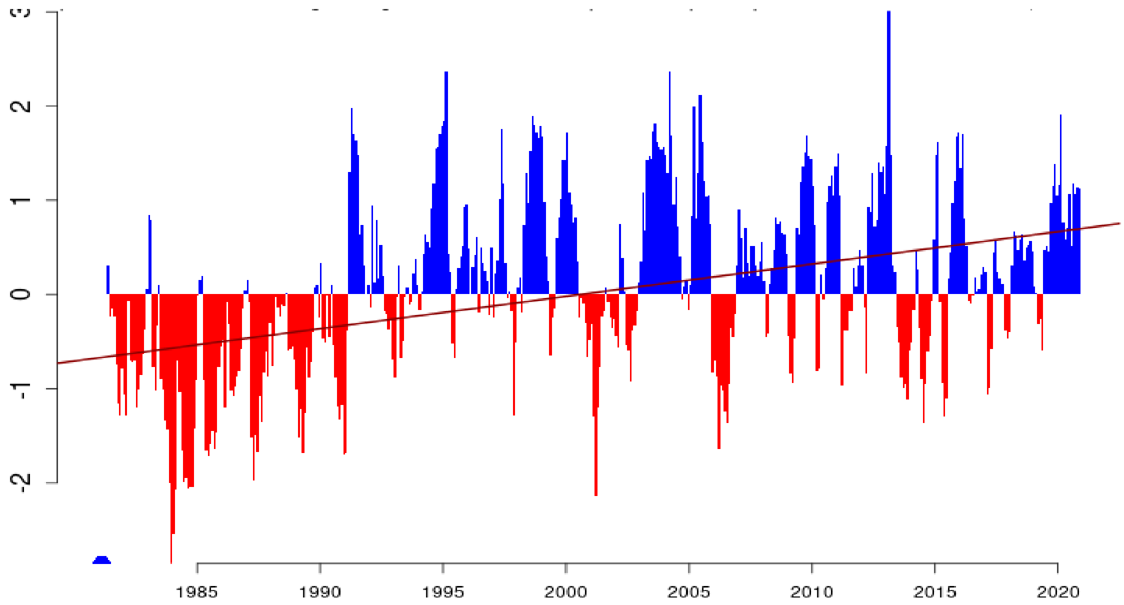

Figure3. Standardised precipitation Evapotranspiration (SPEI6)

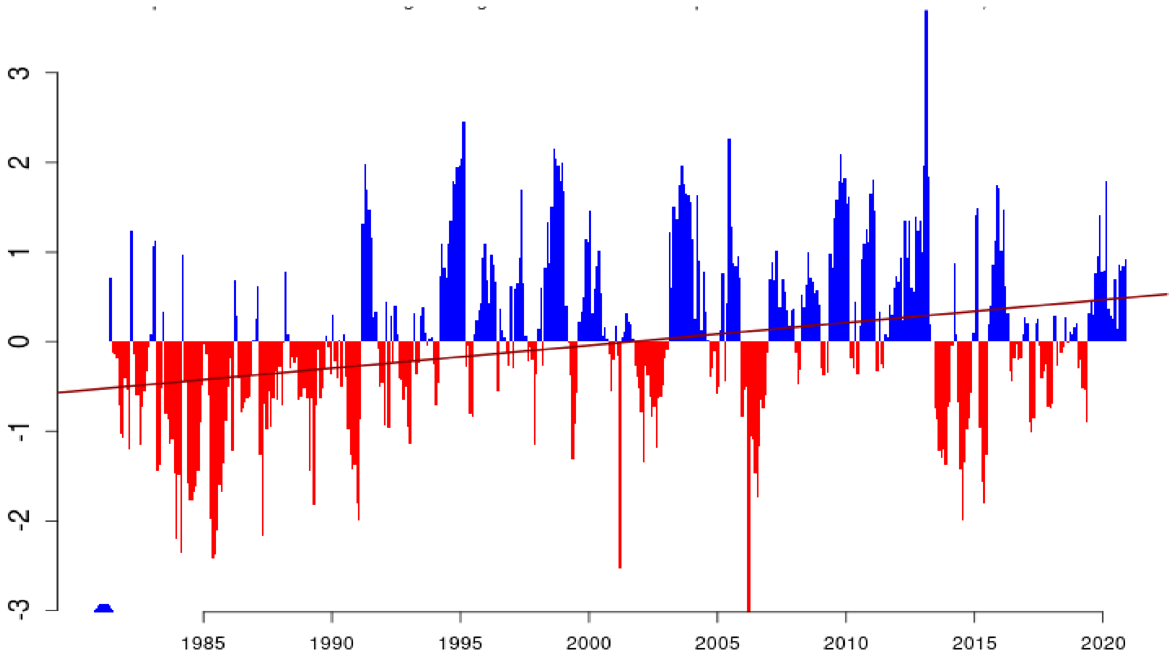

Figure4. Standardised precipitation (SPI6)

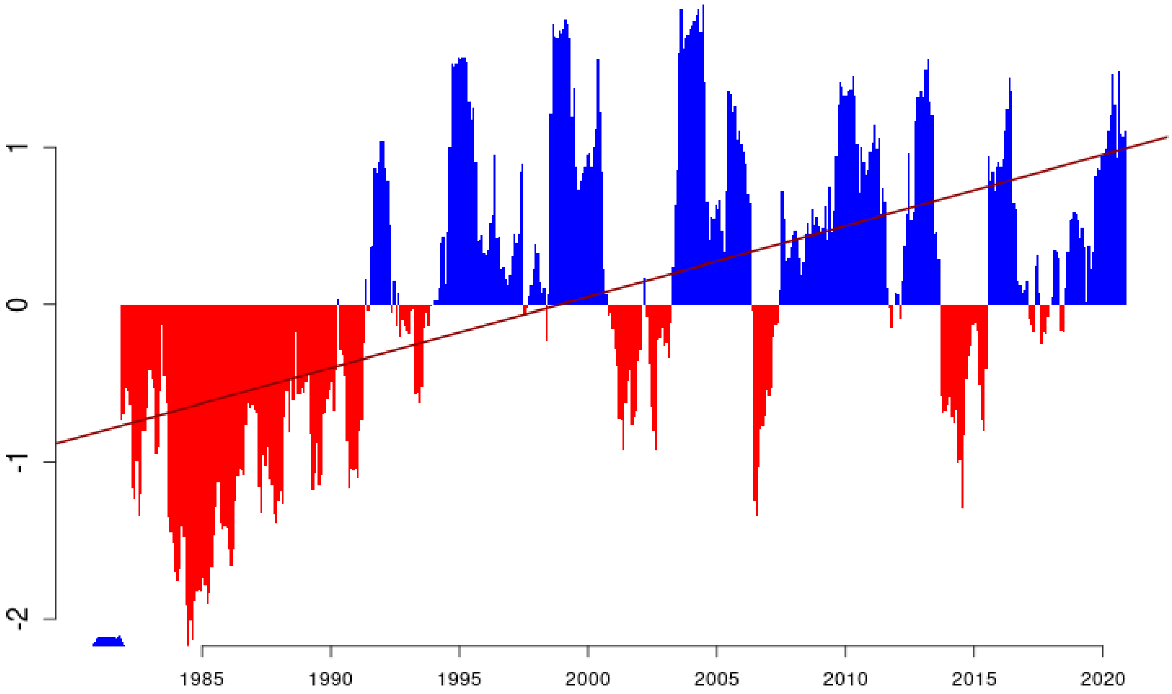

Figure5. Standardised Evapotranspiration (SPEI12)

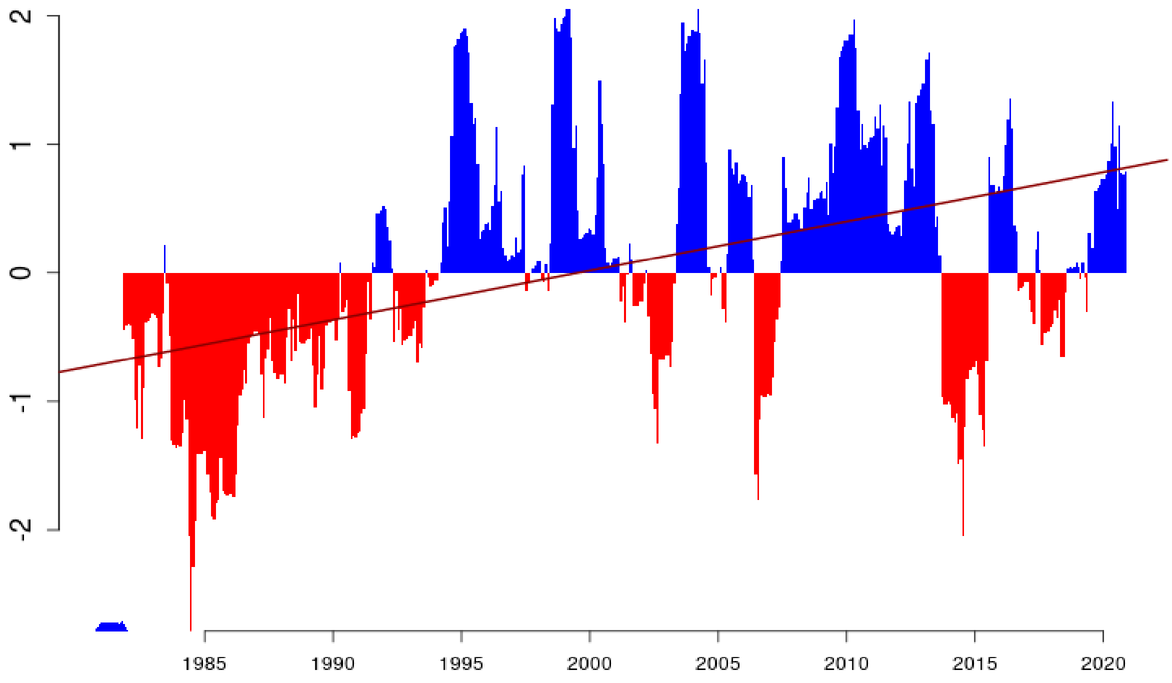

Figure6. Standardised precipitation (SPI12)

Appendix 3. Questionnaire

Name of village:

Household (HH) information

Household head name: profession:

Single [ ] 2. Married [ ] 3. Separated [ ] 4. Divorced [ ] 5. Widowed [ ] 6. Co-habitation [ ]

Sex: M ☐ ☐ c) Age > **30** ☐30-45 ☐45-60 ☐< 60 ☐

Household Size

Sex	0-10 old	11-20 old	21-30 old	31-40 old	>50 old	Total
M						
F						

Have you always been cultivating in the same region?

○ yes ○ No

If no, is the reason due to:

○ Change in climate ○ Government policy

○ Ease access to land ○ Others…………………

Are you a 1. Native [ ] or 2. Settler [ ]

How long have you lived in this community? ………………………(years)

Education level: Islamic school ☐ primary ☐ secondary ☐ tertiary analphabet ☐

Total farm size (acres/hectares): g) Land tenure: Freehold ☐ Leasehold ☐

Major source of livelihood:

What are different services do you get from the area?..?

Do you think the services are increasing or decreasing………………………………?

Why?...

Have you dropped some varieties since you started the farming? Yes □ No □

If Yes, which one?

a. List

Why did you drop those varieties?

Varieties	reasons	Varieties	reasons

What was agricultural calendar

What are your observations about the following climatic parameters for the past 20 years?

i Rainfall amount	Increased [ ]	Decreased [ ]	Same [ ]	Don’t know [ ]
ii Onset (starting) of rainfall	Early onset [ ]	Late onset [ ]	Normal [ ]	Don’t know [ ]
iii Cessation (end) of rainfall	Early [ ]	Late [ ]	Normal [ ]	Don’t know [ ]
iv Length of growing season	Increased [ ]	Decreased [ ]	Same [ ]	Don’t know [ ]
v Temperature	Increased [ ]	Decreased [ ]	Same [ ]	Don’t know [ ]
vi Duration of dry season	Increased [ ]	Decreased [ ]	Normal [ ]	Don’t know [ ]
vii Frequency of prolonged dry spells (no rains in some days during rainfall season)	Increased [ ]	Decreased [ ]	Normal [ ]	Don’t know [ ]

Livestock

Type	Number	Source of fodder/feed	prize		
Cattle (betail)					
Sheep (mouton)					
Chicken (poulets)					

Duck (canard)					
Another					

Crop production

Crop types	Previous year	Cropland(ha)	Inorganic fertilizer per ha in kg	Organic fertilizer per ha in kg	Yield of crops in kg per ha
1.					
2.					
3.					
4.					
5.					

Presence of tree/vegetative species on farm and surroundings

Local name	Scientific name	age	diameter	height	crown	Practices management	indigenous	exogenous

Trees importance in farming system

Scientific name	Climate regulation	Erosion control	Pollination Or honey bee	Cash crop	Crop as subsistence	fodder	Bio mass For fuel	Timber / construction	Fresh-water	Cultural services

SECTION B: LANDUSE AND DRIVERS OF LANDUSE CHANGE

What type(s) of farming systems do you practice?

Shifting cultivation [ ] 2. Crop rotation on same land [ ] 3. Fallow system (leaves land for min 3 yrs before farming it again) [ ] 4. Perennial crops farming like cocoa, cashew [ ] 5. Other, specify ………..

What cover was on the land before you farmed on it for the first time?

Forest [ ] 3. Open vegetation (shrubs and sparse trees) [ ] 3. Grass [ ] 4. Fallow (farmed before and left to regrow [ ] 5. Agroforestry [ ] 6. Tree Plantation [ ] 7. Cash crop [ ] 8. Other, Specify………

What type of farming (kind of crop cultivation) did you practice for the first time on the land?

Mixed Cropping [ ] 2. Mono cropping [ ] 3. Tree plantation [ ] 4. Agroforestry [ ] 5. Other, specify…………………………..

What is your current farming practice (kind of crop cultivation)?

Mixed Cropping [ ] 2. Mono cropping [ ] 3. Tree plantation [ ] 4. Agroforestry [ ] 5. Other, specify…………………………..

What kind(s) of crop(s) have you grown over the last 5 – 10 years?

Tree crops [ ] 2. Cereal like maize [ ] 3. Tubers [ ] 4. Fruits [ ] 5. Vegetables [ ] 6. Other (specify)…………

. What is your current farm size: ……………………… acres

Has your farm size changed (increased or decreased) over the past 5 years?

Yes [ ] 2. No [ ]

If yes what is th

If no, why? …………………………………………………………………………

Do you have plans to expand in future?

Yes [ ] 2. No [ ] 3. Not Sure [ ]

On a scale of 1 – 10, what is the potential of clearing forest if you want to expand your farmland in the future? ……………………….. [1 – not likely and 10 – most likely or very sure]

On a scale of 1 – 10, what is the potential of clearing open vegetation (includes shrubs, grassland) if you want to expand your farmland in the future? ……………

On a scale of 1 – 10, what is the potential of going into Agroforestry (mixing trees and your crops on your farm) or leaving a minimum of 10 trees in an acre of farmland in the future? …………………………

. If no, why …………………………………………………………………

. Do you have plans to change what you are currently planting/cultivating?

Yes [ ] 2. No [ ]

If yes to which type?

. Mixed cropping [ ] 2. Mono Cropping [ ] 3. Agroforestry [ ] 4. Tree Plantation [ ]

Other, specify……………………………………

How long have you been farming? ……………(years)

Do you plant trees in your farm? yes ☐ No ☐

If yes

why?..

List them………………………………………………………………………………

If no why?

Do you leave tree in your farm? Yes ☐ No ☐

If yes

why?..

List them:………………………………………………………………………………

If no ☐ ☐

why?……………………………………………………………………………………

…… Is the tree density or number of trees available on the farm important?

yes.......... No.... ....

Why?...

How about the historical development of woodlots or agroforestry?

Are trees on the farm level increasing or decreasing? Any preferred tree/vegetative species and preferred arrangement/pattern (e.g. hedgerows, woodlot) and location and why?

Which tree species would - you prefer? Why?

Herbicide, insecticide, pesticide and chemical fertilizer

Do you use herbicide, insecticide, pesticide or/ and chemical fertilizer? yes☐ No ☐

If yes, list them……………………………………………………………………………….

Name	Herbicide	Insecticide	pesticide	Chemical fertilizer	Quantite /ha	Frequences using	remanence	Other information